**Virginia Journal of Science** / Volume 72, Issue 3 & 4 / Fall & Winter 2021
doi: 10.25778/fenx-2z64

# Camera Trap Survey Suggests Forestry and Prescribed Burns Attract Wildlife, But May Not Enhance Diversity

M. Sage Vilgats, Ryan Ott, and Stephanie S. Coster

Randolph-Macon College, Richmond, VA

## ABSTRACT

This study explored whether habitat management techniques such as forest thinning and burning promoted biodiversity. Fifteen camera trap stations were established at Fort A.P. Hill in Bowling Green, VA across forest stands with low, medium, and high basal area. Camera traps were deployed for a total of 532 trap nights, and trap success and species diversity were calculated using Shannon's index. At each site, the distance to trafficable roadways and water sources, vegetation composition, and the percent groundcover, canopy cover, and understory were measured. The cameras captured nine species and recorded a total of 398 trap events. Linear regression was used with an information theoretic approach to test and rank several possible models exploring the relationship between trap success and environmental factors. The best model included basal area and displayed an inverse relationship between basal area and trap success, although stands with low basal area had lower levels of diversity.

Keywords: camera trap, basal area, Fort AP Hill

## INTRODUCTION

Prescribed burns and forestry cuts are land management tools that are used to maintain and enhance wildlife habitat (Main and Richardson 2002; Lashley et al. 2011). Cutting and burning reduces the basal area, clears understory, increases sunlight, and promotes early successional vegetation in forests and consequently attracts a variety of wildlife species (Main and Richardson 2002; Lashley et al. 2011). A rich herbaceous layer promoted by fire harbors insects and seeds ideal for passerine granivores, as well as galliformes such as wild turkey (*Meleagris gallopavo)*, and northern bobwhite (*Colinus virginianus)* (Main and Richardson 2002; McCord et al. 2014). This vegetative growth also provides forage and cover for small mammals (Van Lear et al. 2005)

and benefits herbivorous ungulates by enhancing the amount and variety of their food resources (Hobbs and Spowart 1984).

These forest management tools have been used in the southeastern United States to promote and maintain early successional habitats such as pine-grassland (Lashley et al. 2011). Pine-grassland is a rare and important early successional habitat that is home to white-tailed deer (*Odocoileus virginianus)*, northern bobwhite, red-cockaded woodpeckers (*Picoides borealis)*, along with many other species (Van Lear et al. 2005, Mitchell et al. 2006). Pine-grassland systems are known to support high levels of native flora and fauna (Mitchell et al. 2006), with an overstory consisting of relatively few tree species, and a diverse ground cover of herbaceous forbs, shrubs, grasses, and tree seedlings (Gilliam and Platt 2006). These systems are dependent on disturbance regimes and frequent prescribed fires are an important management tool for sustaining this habitat (Mitchell et al. 2006; McIntyre et al. 2019). Frequent fires are necessary to control midstory development, maintain pine dominance, and sustain an herbaceous understory (McIntyre et al. 2019). Sixty-nine percent of the mammal species and a little over one-third of the bird species that inhabit pine-grassland ecosystems forage primarily on or near the ground (Van Lear et al. 2005). Fire regimes are therefore necessary to stimulate an herbaceous understory to support these wildlife species.

Although managed forest stands with a low basal area have been found to attract early successional species, it is unclear whether they support high levels of biodiversity compared to unmanaged forest stands with high basal area. Some studies show that biodiversity is higher in primary unmanaged forests (Bobiec 1998; Gibson et al. 2011), however, a meta-analysis of forest management in Europe found no clear difference in species diversity or species richness among managed and primary forests (Paillet et al. 2010). Managed forests are characterized by frequent disturbances and display a more homogenous tree composition and early successional vegetation, but they lack age dynamics and senescent phases, whereas unmanaged forests display more dead and decaying trees, older and larger trees, and root plates (Paillet et al. 2010). Overall, there is still some debate regarding the effects of forest management on biodiversity. On a local level, unmanaged forests are said to generally contain more species than managed forests, but there is some inconsistency in the literature as to whether this is true or not (Väisänen et al. 1993; Bobiec 1998; Paillet et al. 2010).

In addition to forest management, other landscape features can attract or deter wildlife, such as water, roadways, and vegetative structure. Roadways may deter animals as a result of traffic or a lack of cover, but roads may also attract animals for ease of movement. The response varies by type of road and species, as bobcats (*Lynx rufus)* are found in areas of low road density (Litvaitis et al. 2006) or even deterred by roads (Kelly and Holub 2008) while cougars (*Puma concolor)* avoid two-lane paved roads but may use unpaved roads to facilitate movement (Dickson et al. 2005). Riparian areas also provide resources that may attract a variety of animals. Even when not strictly dependent on riparian areas, a higher diversity of small mammal species is caught along streams in a forested ecosystem (Anthony et al. 1987). Herbaceous vegetation and young shrubs may attract White-tailed Deer and other wildlife as they offer high quality forage, in terms of digestion and crude protein (Main and Richardson 2002).

Camera trapping is a method that can be used to monitor wildlife abundance and diversity, as well as better understand how forest management and natural landscape features attract or deter wildlife (Brodie et al. 2015; Steenweg et al. 2017). Over the past decade, camera traps have emerged as a powerful tool in wildlife research as they noninvasively capture information about wildlife presence and allow long term monitoring in the field with less effort (e.g., Moruzzi et al. 2002; Kelly and Holub 2008; Rovero et al. 2013; du Preez et al. 2014). Camera traps are relatively inexpensive compared to live trapping efforts and can be useful for wildlife monitoring programs (McShea et al. 2016). In addition, compared to line transects, camera traps are better able to record rare and elusive species (Tobler et al. 2008). Camera-trapping is becoming one of the most efficient means for mammal inventories and population studies (Silveira et al. 2003; Steenweg et al. 2017). For example, camera traps have been deployed in the Udzungwa Mountains of Tanzania to estimate the density of the elusive Harvey's duiker *(Cephalophus harveyi)* and were shown to be a valid index of density of the target species (Rovero and Marshall 2009). Camera traps have also been used to survey carnivore distribution in Vermont (Moruzzi et al. 2002), as well as inventory medium and large-sized terrestrial mammals in tropical forests (Tobler et al. 2008), and to monitor wildlife response to recreational trail building (Miller et al. 2020).

In this study, we used camera traps to explore whether forest management techniques such as forest thinning, and prescribed burns promoted biodiversity in a pine savannah ecosystem located in the eastern piedmont region of Virginia. Specifically, we measured camera trap success and species diversity across stands of varying basal areas (low, medium, and high). We also explored the relationship between camera trap success and natural landscape features including vegetative characteristics to investigate what attracts wildlife to these sites. We predicted that camera trap success and diversity would be highest in a low basal area, with a high percent of grasses, close proximity to water, and greater distance from roads. A low basal area would allow sunlight to reach the forest floor and promote the growth of a variety of vegetation. A high percent of grasses and close proximity to water would provide necessary nutritional resources, and a greater distance from roads would limit anthropogenic disturbance and provide more cover.

## MATERIALS AND METHODS

### Field-Site Description

The study area was located within Fort A.P. Hill (APH), a 30,329 ha military training installation (U.S. Army) in the upper Coastal Plain of Caroline County, VA. APH is 80% forested with natural re-growth post farming and on-going forest management (Bellows et al. 2001). The study area hosts a variety of habitat types, such as old fields, wetlands, mixed pine and hardwood forest, and pine-dominated stands with open understory. The dominant pines in the study area are loblolly pine *(Pinus taeda)* and Virginia scrub pine *(Pinus virginiana)* and the dominant hardwoods are southern red oak *(Quercus falcata)*, northern red oak *(Q. rubra)*, sweetgum *(Liquidambar styraciflua)*, red maple *(Acer rubrum)*, and tulip poplar *(Liriodendron tuilipifera)*. Biologists and foresters at APH actively manage the area using prescribed burns and forestry cuts to promote habitat diversity. In some pine-dominated stands, silviculture treatments with yearly prescribed burns have been used to promote early successional habitat for northern bobwhite. In

mixed pine and hardwood forests, forest thinning and burning is also implemented with longer regeneration periods.

Camera trap sites

We identified forest stands with low (20-35 $ft^2acre^{-1}$), medium (50-90 $ft^2acre^{-1}$) and high (110-130 $ft^2acre^{-1}$) basal areas and set up five camera trap sites in each stand for a total of 15 camera sites (Fig. 1). The low basal area stand had been thinned and burned during the previous winter. The medium and high basal area stands had not been burned for at least 2 years prior to the study. To maintain trap independence, each site was located at least 300 meters apart. We deployed camera traps for six weeks from 18 June – 26 July 2018. We used infrared Moultrie Panoramic 150 game cameras, set to a panoramic display with a 1-minute delay between photographs. We attached cameras to a tree around knee height, approximately 3-5 m away from a baited tree. The camera placement was made to ensure that both large and small animals could be detected and captured. To attract a diverse range of taxa, we set up a scent lure of anise oil and two types of bait, a fish bait to attract carnivores, and a mound of corn to attract herbivores. During the initial set-up, we cleared a small patch of ground at the base of each bait tree and left a small mound of corn. Additionally, we baited each site by nailing a can of anchovies (with holes in it) to the bait tree. During the third week of the study, we replenished the corn and anise oil baits, and we also spread chunks of American gizzard shad *(Dorosoma cepedianum)* around the bait tree. To reduce likelihood of wildlife running away with bait without being detected, in the $4^{th}$ week we placed new chunks of American Gizzard Shad in suet cages nailed to each bait tree. In the $5^{th}$ week of the study, we replenished the corn and anise baits again and refilled cages with American Gizzard Shad if needed. We checked camera traps weekly to collect pictures and ensure cameras were properly functioning. We transferred pictures on site from camera SD cards to a laptop to be analyzed later.

Vegetation Sampling

To explore whether landscape features and vegetative characteristics influence trap success, we measured basal area, the distance to trafficable roadways and water sources, vegetation composition, and the percent groundcover, canopy cover, and understory at each camera site. We measured basal area using a forestry wedge prism. We used ArcMap 10.7.1 (ESRI, Redlands, CA) to measure the shortest distance between each site and the nearest trafficable road and water source. We broke down vegetative composition into herbaceous forbs, grass, shrubs, and duff/litter. To measure the percent cover of the vegetation types, we established circular plots using a hula hoop (area of 0.55 $m^2$) at each site. We chose the location of the plots to be representative of the vegetation of the surrounding area, therefore the center of the plots ranged from 1.3 – 7.2 m from the bait tree. We also identified the dominant plant species in each plot and used Pearson's correlation to examine the relationship between the percent herbaceous forbs and basal area.

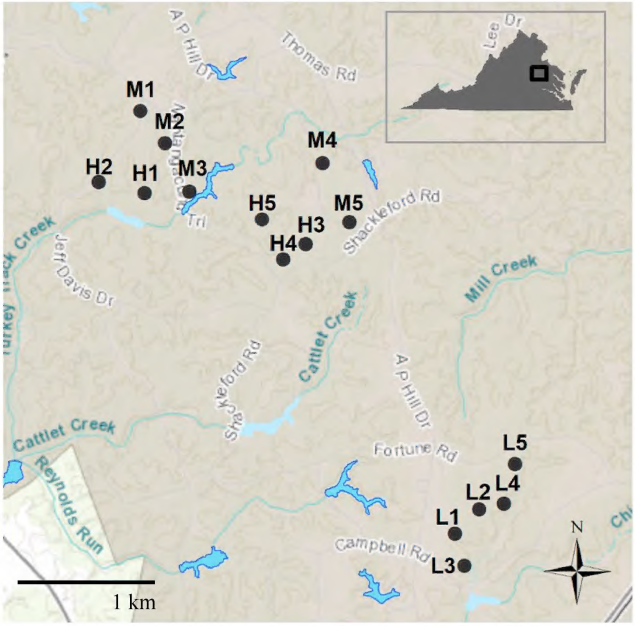



**FIGURE 1**. Location of the camera trap sites, indicated by numbered dots in areas of low (L), medium (M), and high (H) basal area, at Fort A.P. Hill in Caroline County, VA.

<u>Data Analysis</u>

We reviewed each photograph and recorded the number of trap events, the species captured, any false positives (pictures with no animals present), and the date and time of each event. A trap event was defined as one individual animal identified in a photograph; if we identified two or more individuals in the same photograph it was counted as two (or more) trap events. To ensure each trap event was independent, we eliminated photographs of the same species taken within a 30-minute interval. We determined the trap effort by summing the number of nights each trap was running and subtracting the number of days a camera malfunctioned. We calculated trap success as the number of trap events per 100 trap nights. We calculated overall trap success and trap success by camera station. We then examined trap success by basal area using a one-way ANOVA. We also calculated species diversity using the Shannon's diversity index for each basal area (Shannon 1948),

$$H = -\sum_{i=1}^{k} P_i ln P_i$$

where H is the Shannon index value, $P_i$ is the proportion of the population made up of the species *i, ln* is the natural logarithm, and *k* is the number of species in the community. We used an

information-theoretic approach with linear regression to test and rank seven possible models exploring what factors most influenced trap success. We chose to employ an information-theoretic approach as opposed to other multivariate analyses to avoid data dredging and instead rank well-reasoned *a priori* models based on which provides the best inference from the data collected (Burnham and Anderson 2001). Model selection seeks parsimony by balancing bias and precision (Burnham and Anderson 2001). The covariates included basal area, stand type (softwood, hardwood or mixed), percent groundcover, percent grasses and shrubs, and distances to roads and water (See Table 1 for all models). We used package lmtest (Zeileis and Hothorn 2002) and nortest (Gross and Ligges 2015) in R (R Core Team 2016) to test the assumptions of linear regression, including the Breusch-Pagan test to assess homoscedasticity and the Anderson-Darling and Shapiro-Wilk tests to assess the distribution of residuals.

## RESULTS

### Trap Success

After 532 trap nights, the cameras captured 9 different species in a total of 398 trap events (Fig. 2). The overall trap success was 74.81 trap events per 100 trap nights (Supplementary Table S1). The average trap success for all species at each site was 4.99 / 100 trap nights (range 0.94 – 16.73; Supplementary file Fig. S2). Of the 398 events, White-tailed deer was the dominant species (213 trap events), followed by crows *(Corvus spp.)* and racoons *(Procyon lotor)* (Fig. 2).

### Presence and Diversity

Trap success in the low basal area was significantly higher than the trap success in medium and high basal area forest ($p = 0.03$, $F(2,12) = 9.36$; Fig. 3). Camera traps that were in low basal area forest captured a total of 6 species and 241 trap events with an average trap success of 9.21 trap events per 100 trap nights (Table 2). Cameras in medium basal area forest captured 8 species and 58 events, and those in high basal area forest captured 8 species and 84 trap events. Cameras located in the high basal area forest recorded a higher level of diversity ($H = 1.47$) than those in low basal area forest ($H = 1.11$) and medium basal area forest ($H = 1.01$) although the error bars overlapped in the high and medium basal area forest (Fig. 4). The number of trap events of early successional species (e.g., white-tailed deer and wild turkey) decreased in higher basal area stands, whereas the number of trap events of raccoons increased with basal area (Table 2). The number of coyote (*Canis latrans*) trap events decreased as basal area increased ($R^2 = 0.51$, $F(1,13) = 13.43$, $p = 0.003$; Supplementary Fig. S2).

**TABLE 1**. Models used in linear regression to predict trap success ranked in order of weight and including model selection statistics.

| Model | logLik | AICc | ΔAIC | weight |
|---|---|---|---|---|
| Basal Area | -13.39 | 34.96 | 0.00 | 0.71 |
| Null | -16.64 | 38.28 | 3.32 | 0.14 |
| Percent Groundcover | -15.51 | 39.20 | 4.24 | 0.09 |
| Distances to Roads + Water | -14.36 | 40.72 | 5.76 | 0.04 |
| Basal Area + Stand Type | -13.16 | 42.98 | 8.02 | 0.01 |
| Stand Type + Percent Grasses + Percent | -10.29 | 43.08 | 8.12 | 0.01 |
| Global Model | -2.43 | 79.87 | 44.91 | 0.00 |

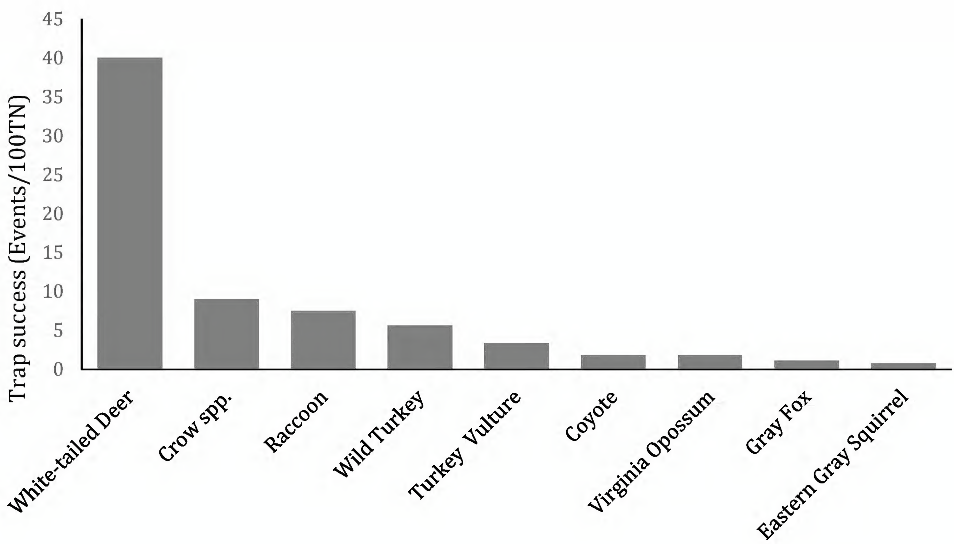



**FIGURE 2**. Trap success of the nine species captured by 15 camera trap sites set in Fort A.P. Hill, Caroline County, VA. Trap success defined as the number of individuals identified (trap events) per 100 trap nights (TN).

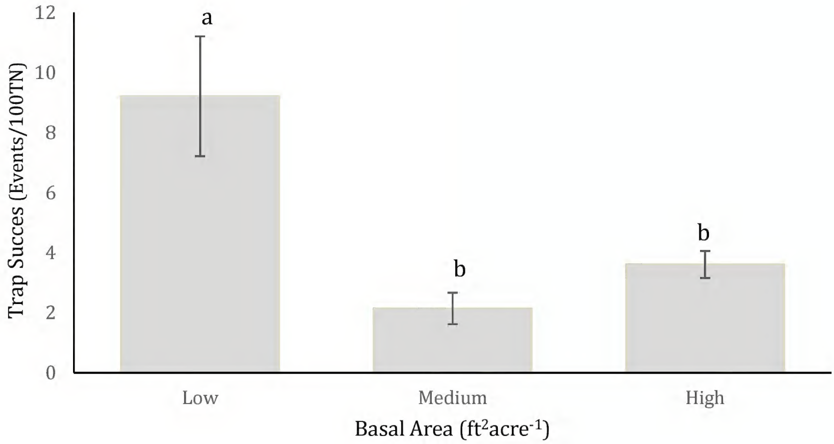



**FIGURE 3**. Average trap success of camera trap sites set up in in low (20-35 $ft^2acre^{-1}$), medium (50-90 $ft^2acre^{-1}$), and high (110-130 $ft^2acre^{-1}$) basal area stands with error bars that represent standard error. Each stand had 5 camera trap sites. A one-way ANOVA found trap success was significantly different across stands ($p = 0.03$, $F\ (2,12) = 9.36$). A Tukey's post-hoc test evaluated the difference between levels and levels that are not significantly different are represented by the same letter.

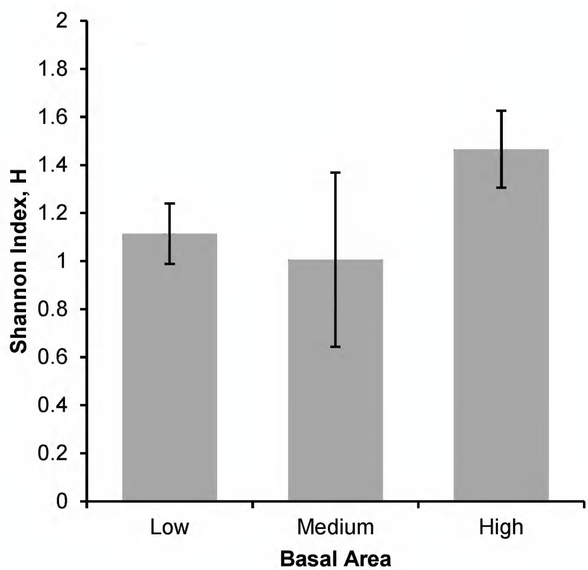



**FIGURE 4.** Diversity values of camera trap sites set in in low (20-35 $ft^2acre^{-1}$), medium (50-90 $ft^2acre^{-1}$), and high (110-130 $ft^2acre^{-1}$) basal area stands. Diversity values were calculated using Shannon's Diversity Index. Each stand had 5 camera trap sites.

**TABLE 2.** Presence of species by basal area. Trap events for each species captured in low, medium, and high basal area stands.

| **Species (common name)** | **Low** | **Medium** | **High** |
|---|---|---|---|
| *Odocoileus virginianus* (White-tailed Deer) | 152 | 41 | 20 |
| *Corvus* spp. (Crow) | 44 | 2 | 2 |
| *Meleagris gallopavo* (Wild Turkey) | 28 | 2 | 0 |
| *Procyon lotor* (Raccoon) | 4 | 5 | 35 |
| *Cathartes aura* (Turkey Vulture) | 6 | 3 | 9 |
| *Canis latrans* (Coyote) | 7 | 2 | 1 |
| *Didelphis virginiana* (Virginia Opossum) | 0 | 0 | 10 |
| *Urocyon cinereoargenteus* Schreber (Common Gray Fox) | 0 | 1 | 4 |
| *Sciurus carolinensis* Gmelin (Eastern Gray Squirrel) | 0 | 1 | 3 |
| Total trap events | 241 | 58 | 84 |

Vegetation Characteristics

The vegetative composition differed at each trap site, with a greater percent of herbaceous forbs in low basal areas and a greater percent of duff/litter in high basal areas (Supplementary Fig. S3). We found a negative correlation between basal area and herbaceous forbs across sites ($r(13) = -0.86$, $p = 0.000033$, Supplementary Fig. S4). The dominant plant species varied across all sites, although in the low basal areas, the dominant species were primarily herbaceous forbs (48%) and included either fireweed *(Chamaenerion angustifolium)* or American pokeweed *(Phytolacca americana)* (Supplementary Table S2). Sites in the medium basal area had the highest percent of shrubs (38%) and grasses (33%) on average, compared to sites in low and high basal area. The sites in the high basal area had the most duff/litter (70.8%) on average and vegetation plots at these sites usually consisted of only one or two plant species, unlike sites in the other basal areas.

With regards to the landscape features that best predicts trap success, we log transformed trap success and basal area and square root transformed percent shrubs and percent grass to meet the assumptions of linear regression. After these transformations, the assumptions of normality and homoscedasticity were confirmed for all models. We found that the basal area model ranked

the highest, followed by the null model, and both of these models had a ΔAIC < 4. Basal area exhibited an inverse relationship with trap success ($R^2 = 0.30$, $F(1,13) = 7.049$, $p = 0.0198$; Fig. 5). The other models that included vegetative and landscape covariates were not predictive of trap success (Table 1).

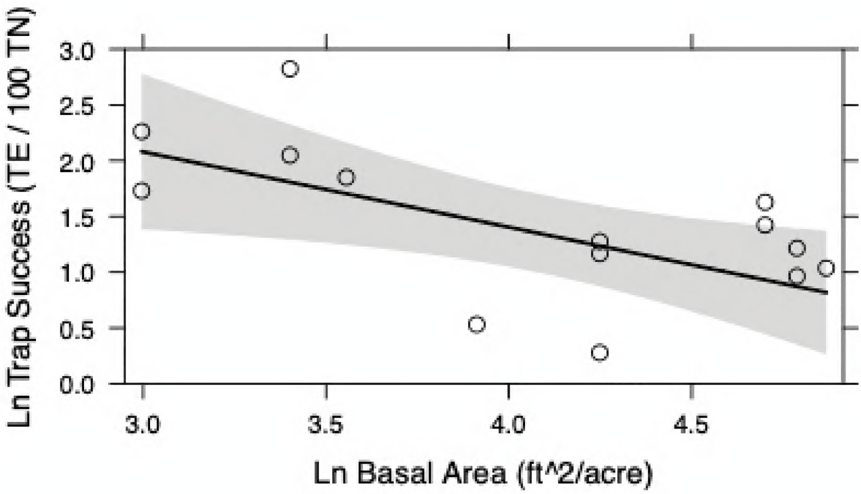



**FIGURE 5**. Effects plot of the top model with basal area regressed on trap success ($R^2 = 0.30$, $F(1,13) = 7.049$, $p = 0.0198$). Black line represents the predictive model with 95% confidence interval shaded.

## DISCUSSION

Our results suggest that low basal area sites attract higher numbers of wildlife, although these stands have lower levels of diversity compared to stands with a high basal area. Additionally, contrary to our hypotheses, vegetative and landscape features were not highly predictive of trap success, instead basal area alone was the most predictive model. We found a negative correlation between basal area and herbaceous forbs, confirming that forest thinning and burning promotes sunlight and increases ground vegetation.

Actively managed open canopy forest may attract wildlife for a number of reasons. Forest thinning and prescribed burning opens the forest canopy and stimulates forage production (Van Lear et al. 2005; Lashley et al. 2011), as well as fosters high levels of plant diversity (Mitchell et al. 2006). Plant regrowth after a fire has been found to be more palatable and of a higher nutritional quality for mammalian herbivores (Eby et al. 2014; Cherry et al. 2017). Along the coastal plain in the southeastern United States, studies have found that burning can increase nutrients such as Phosphorus in the soil, which is needed for antler development (Grasman and Hellgren 1993; Van Lear and Harlow 2002). In addition, a 2011 study found that canopy reduction combined with

prescribed burning increased forage availability for white-tailed deer, and that retention cuts followed by prescribed fire maintained a large nutritional carrying capacity (Lashley et al. 2011). An open-canopy forest structure is also attractive to herbivores including small mammals, ground-dwelling birds and birds that forage in open spaces within forests (Mengak et al. 1989; Mitchell et al. 2006).

In our study the high trap success in low basal areas was predominantly from species that prefer early successional habitats such as white-tailed deer, crow, and wild turkey. In addition, the trap success of coyotes was also high in low basal areas. This is likely due to a connection of predator and prey, where coyotes were attracted to these sites because of the high numbers of white-tailed deer and turkey. In the southeastern United States coyotes are a top predator of white-tailed deer and have been linked to declines in fawn survival and population growth (Cherry et al. 2017). Our results are similar to Richer et al. (2002) and Cherry et al. (2017), that both found greater coyote abundance in open areas compared to forests. These studies suggest that coyotes are poorly adapted to hunting in dense forests (Richer et al. 2002) and that their higher abundance in open areas is likely due to utilization of prey such as rodents and white-tailed deer (Cherry et al. 2017).

Unlike open canopy forests with low basal area, higher basal area forests have a thicker canopy that offers shade but limits vegetative ground cover (Mitchell et al. 2006). These forests may have features besides ground vegetation that appeal to a variety of wildlife species. The limited ground cover in dense forests may result in open pathways for easier movement. In addition to movement, a high tree density with understory shrubs and coarse woody debris provides important resources and shelter for certain species. For example, although gray fox *(Urocyon cinereoargenteus)* and racoons are both habitat generalists, they tend to spend more time in mature forests rather than open habitats (Haroldson and Fritzell 1984; Chamberlain et al. 2002). In this study both gray fox and racoons were photographed more in high basal area stands.

The other vegetative and landscape factors we tested may have been less predictive of trap success for a number of reasons. While herbaceous forbs were predominantly found in the low basal area sites, grasses and shrubs were found across low, medium, and high basal areas, which makes it harder to determine their direct influence on trap success. In addition, Fort A.P. Hill has a high density of roads with relatively low traffic levels, therefore, wildlife may be acclimated to or undeterred by roads. Kelly and Holub (2008) found higher bobcat camera trap success as the distance to the main road increased but found no other significant relationships between roads and camera trap success in other carnivores. Additionally, wetlands and riparian areas are abundant in this landscape and may not be a limiting factor that drives habitat preferences in this area.

In this study we baited the camera traps in order to maximize trap success and the baits used may have introduced some bias. Initially, with the bait of corn, anise oil, and anchovies, we found that corn was the main attractant. We primarily recorded white-tailed deer and wild turkey eating the corn at the sites during this period. When we put out the gizzard shad, we began capturing more omnivores and scavengers, including turkey vulture *(Cathartes aura)* and Virginia opossum *(Didelphis virginiana)*, and we noticed an increase in the number of raccoons. Although somewhat controversial (Rocha et al. 2016), we felt that the advantages of using bait outweighed

the costs, in that adding bait increases capture probability, facilitates identification as an organism stops to inspects the bait, and can aid in age and sex determination (du Preez et al. 2014; Austin et al. 2017).

Overall, our results suggest that open forests promote early successional habitat and attracts wildlife but may not maximize species diversity. Low basal area stands have thick groundcover which provides quality herbaceous forage and attracts greater numbers of wildlife, while high basal area stands have more open pathways for efficient movement, provide better habitat for species relying on trees for shelter and may support higher levels of diversity. Similar to our findings, a 2001 small mammal survey at APH found higher small mammal numbers in open canopy sites but higher species richness in closed canopy sites (Bellows et al. 2001). Ultimately, to attract more wildlife and promote diversity within wildlife populations, natural resource managers should aim to create a heterogeneous landscape with forested patches of varying tree densities and a variety of herbaceous food resources.

## LITERATURE CITED

Anthony, R. G., E. D. Forsman, G. A. Green, et al. 1987. Small mammal populations in riparian zones of different-aged coniferous forests. The Murrelet 68:94–102. https://doi.org/10.2307/3534114

Austin, C., K. Tuft, D. Ramp, et al. 2017. Bait preference for remote camera trap studies of the endangered northern quoll (*Dasyurus hallucatus*). Australian Mammalogy 39:72–77. https://doi.org/10.1071/AM15053

Bellows, A. S., J. Mitchell, J. F. Pagels, and H. Mansfield, H. 2001. Mammals of Fort A. P. Hill, Caroline County, Virginia and vicinity. Virginia Journal of Science 52:163–226. https://doi.org/10.25778/4xh3-fh93

Bobiec, A. 1998. The mosaic diversity of field layer vegetation in the natural and exploited forests of Bialowieża. Plant Ecology 136:175–175. https://doi.org/10.1023/A:1009736823553

Brodie, J. F., A. J. Giordano, E. F. Zipkin, et al. 2015. Correlation and persistence of hunting and logging impacts on tropical rainforest mammals. Conservation Biology 29:110–121. https://doi.org/10.1111/cobi.12389

Burnham, K. P. and D. R. Anderson. 2001. Kullback-Leibler information as a basis for strong inference in ecological studies. Wildlife Research 28:111–120. https://doi.org/10.1071/WR99107

Chamberlain, M. J., L. M. Conner, and B. D. Leopold. 2002. Seasonal habitat selection by raccoons (*Procyon lotor*) in intensively managed pine forests of central Mississippi. The American Midland Naturalist 147:102–108. https://doi.org/10.1674/0003-0031(2002)147[0102:SHSBRP]2.0.CO;2

Cherry, M. J., R. J. Warren, and L. M. Conner. 2017. Fire-mediated foraging tradeoffs in white-tailed deer. Ecosphere 8:e01784. https://vtechworks.lib.vt.edu/handle/10919/78476

Dickson, B. G., J. S. Jenness, and P. Beier. 2005. Influence of vegetation, topography, and roads on cougar movement in southern California. The Journal of Wildlife Management 69:264–276. https://doi.org/10.2193/0022-541X(2005)069%3C0264:IOVTAR%3E2.0.CO;2

du Preez, B. D., A. J. Loveridge, and D. W. Macdonald. 2014. To bait or not to bait: A comparison of camera-trapping methods for estimating leopard *Panthera pardus* density. Biological Conservation 176:153–161. https://doi.org/10.1016/j.biocon.2014.05.021

Eby, S. L., T. M. Anderson, E. P. Mayemba, and M. E. Ritchie. 2014. The effect of fire on habitat selection of mammalian herbivores: The role of body size and vegetation characteristics. Journal of Animal Ecology 83:1196–1205. https://doi.org/10.1111/1365-2656.12221

Gibson, L., T. M. Lee, L. P. Koh, et al. 2011. Primary forests are irreplaceable for sustaining tropical biodiversity. Nature 478:378. https://doi.org/10.1038/nature10425

Gilliam, F. S. and W. J. Platt. 2006. Conservation and restoration of the *Pinus palustris* ecosystem. Applied Vegetation Science 9:7–10. https://doi.org/10.1111/j.1654-109X.2006.tb00650.x

Grasman, B. T. and E. C. Hellgren. 1993. Phosophorus nutrition in white-tailed deer: nutrient balance, physiological responses, and antler growth. Ecology 74:2279–2296. https://doi.org/10.2307/1939581

Gross, J. and U. Ligges. 2015. nortest: Tests for normality. In: R package version 1.0-4. https://CRAN.R-project.org/package=nortest

Haroldson, K. J. and E. K. Fritzell. 1984. Home ranges, activity, and habitat use by gray foxes in an oak-hickory forest. The Journal of Wildlife Management 48:222–227. https://doi.org/10.2307/3808476

Hobbs, N. T. and R. A. Spowart. 1984. Effects of prescribed fire on nutrition of mountain sheep and mule deer during winter and spring. The Journal of Wildlife Management 551–560. https://doi.org/10.2307/3801188

Kelly, M. J. and E. L. Holub. 2008. Camera trapping of carnivores: Trap success among camera types and across species, and habitat selection by species, on Salt Pond Mountain, Giles County, Virginia. Northeastern Naturalist 15:249–262. https://doi.org/10.1656/1092-6194(2008)15[249:CTOCTS]2.0.CO;2

Lashley, M. A., C. A. Harper, G. E. Bates, and P. D. Keyser. 2011. Forage availability for white-tailed deer following silvicultural treatments in hardwood forests. The Journal of Wildlife Management 75:1467–1476. https://doi.org/10.1002/jwmg.176

Litvaitis, J. A., T. P. Tash, and C. L. Stevens. 2006. The rise and fall of bobcat populations in New Hampshire: Relevance of historical harvests to understanding current patterns of

abundance and distribution. Biological Conservation 128:517–528. https://doi.org/10.1016/j.biocon.2005.10.019

Main, M. B. and L. W. Richardson. 2002. Response of wildlife to prescribed fire in southwest Florida pine flatwoods. Wildlife Society Bulletin (1973-2006) 30:213–221. https://www.jstor.org/stable/pdf/3784656.pdf

McCord, J. M., C. A. Harper, and C. H. Greenberg. 2014. Brood cover and food resources for wild turkeys following silvicultural treatments in mature upland hardwoods. Wildlife Society Bulletin 38:265–272. https://doi.org/10.1002/wsb.403

McIntyre, R. K., L. M. Conner, S. B. Jack, et al. 2019. Wildlife habitat condition in open pine woodlands: Field data to refine management targets. Forest Ecology and Management 437:282–294. https://doi.org/10.1016/j.foreco.2019.01.045

McShea, W. J., T. Forrester, R. Costello, et al. 2016. Volunteer-run cameras as distributed sensors for macrosystem mammal research. Landscape Ecology 31:55–66. https://doi.org/10.1007/s10980-015-0262-9

Mengak, M. T., D. C. Guynn, and D. H. Van Lear. 1989. Ecological implications of Loblolly Pine regeneration for small mammal communities. for sci 35:503–514. https://doi.org/10.1093/forestscience/35.2.503

Miller, A. B., R. Kays, and Y-F. Leung. 2020. Wildlife response to recreational trail building: An experimental method and Appalachian case study. Journal for Nature Conservation 56: 125815. https://doi.org/10.1016/j.jnc.2020.125815

Mitchell, R. J., J. K. Hiers, J. J. O'Brien, et al. 2006. Silviculture that sustains: The nexus between silviculture, frequent prescribed fire, and conservation of biodiversity in longleaf pine forests of the southeastern United States. Canadian Journal of Forest Research 36:2724–2736. https://doi.org/10.1139/x06-100

Moruzzi, T. L., T. K. Fuller, R. M. DeGraaf, et al. 2002. Assessing remotely triggered cameras for surveying carnivore distribution. Wildlife Society Bulletin (1973-2006) 30:380–386. https://www.jstor.org/stable/3784494

Paillet, Y., L. Bergès, L., J. Hjältén, et al. 2010. Biodiversity differences between managed and unmanaged forests: Meta-analysis of species richness in Europe. Conservation Biology 24:101–112. https://doi.org/10.1111/j.1523-1739.2009.01399.x

R Core Team. 2016. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Richer, M-C., M. Crête, J-P. Ouellet, et al. 2002. The low performance of forest versus rural Coyotes in northeastern North America: inequality between presence and availability of prey. Ecoscience 9:44–54. https://doi.org/10.1080/11956860.2002.11682689

Rocha, D. G., E. E. Ramalho, and W. E. Magnusson. 2016. Baiting for carnivores might negatively affect capture rates of prey species in camera-trap studies. Journal of Zoology 300:205–212. https://doi.org/10.1111/jzo.12372

Rovero, F. and A. R. Marshall. 2009. Camera trapping photographic rate as an index of density in forest ungulates. Journal of Applied Ecology 46:1011–1017. https://doi.org/10.1111/j.1365-2664.2009.01705.x

Rovero, F., F. Zimmermann, D. Berzi, and P. Meek. 2013. “Which camera trap type and how many do I need?” A review of camera features and study designs for a range of wildlife research applications. Hystrix, the Italian Journal of Mammalogy 24:148–156. https://doi.org/10.4404/hystrix-24.2-8789

Shannon, C. E. 1948. A mathematical theory of communication. Bell System Technical Journal 27:379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Silveira, L., A. T. Jácomo, and J. A. F. Diniz-Filho. 2003. Camera trap, line transect census and track surveys: A comparative evaluation. Biological Conservation 114:351–355. https://doi.org/10.1016/S0006-3207(03)00063-6

Steenweg, R., M. Hebblewhite, R. Kays, et al. 2017. Scaling-up camera traps: Monitoring the planet’s biodiversity with networks of remote sensors. Frontiers in Ecology and the Environment 15:26–34. https://doi.org/10.1002/fee.1448

Tobler, M. W., S. E. Carrillo-Percastegui, R. Leite Pitman, et al. 2008. An evaluation of camera traps for inventorying large-and medium-sized terrestrial rainforest mammals. Animal Conservation 11:169–178. https://doi.org/10.1111/j.1469-1795.2008.00169.x

Väisänen, R., O. Biström, and K. Heliövaara. 1993. Sub-cortical Coleoptera in dead pines and spruces: Is primeval species composition maintained in managed forests? Biodiversity & Conservation 2:95–113. https://doi.org/10.1007/BF00056127

Van Lear, D. H., W. D. Carroll, P. R. Kapeluck, and R. Johnson. 2005. History and restoration of the longleaf pine-grassland ecosystem: Implications for species at risk. Forest Ecology and Management 211:150–165. https://doi.org/10.1016/j.foreco.2005.02.014

Van Lear, D. H. and R. F. Harlow. 2002. Fire in the eastern United States: Influence on wildlife habitat. In: Ford, W. Mark; Russell, Kevin R.; Moorman, Christopher E., eds. Proceedings: The role of fire for nongame wildlife management and community restoration: Traditional uses and new directions. Gen. Tech. Rep. NE-288. Newtown Square, PA: US Dept of Agriculture, Forest Service, Northeastern Research Station. 2-10. 9 pp. https://www.nrs.fs.fed.us/pubs/gtr/gtr_ne288/gtr_ne288_002.pdf

Zeileis, A. and T. Hothorn. 2002. Diagnostic checking in regression relationships. In: R News 2(3). https://CRAN.R-project.org/doc/Rnews/

## APPENDIX: Supplementary Tables and Figures

**TABLE S1.** Trap events and calculated trap success for each species captured during the study. 15 total camera traps and 532 trap nights.

| Species (common name) | Trap Events | Trap Success |
|---|---|---|
| *Odocoileus virginianus* (White-tailed Deer) | 213 | 40.04 |
| *Corvus* spp. (Crow) | 48 | 9.02 |
| *Procyon lotor* (Raccoon) | 40 | 7.52 |
| *Meleagris gallopavo* (Wild Turkey) | 30 | 5.64 |
| *Cathartes aura* (Turkey Vulture) | 18 | 3.38 |
| *Canis latrans* (Coyote) | 10 | 1.88 |
| *Didelphis virginiana* (Virginia Opossum) | 10 | 1.88 |
| *Urocyon cinereoargenteus* (Common Gray Fox) | 6 | 1.13 |
| *Sciurus carolinensis* (Eastern Gray Squirrel) | 4 | 0.75 |
| unknown | 19 | - |
| Total | 398 | 74.81 |

**TABLE S2**. Percent cover of herbaceous forbs, shrubs, grasses, duff/litter, and the top three dominant plant species at each camera trap site, in areas of low (L), medium (M), and high (H) basal areas.

| ID | Herbaceous Forbs | Shrubs | Grasses | Duff/Litter | Dominant Plant Species |
|---|---|---|---|---|---|
| L1 | 35 | 20 | 10 | 35 | *Chamerion angustifolium* Holub (Fireweed), *Phytolacca americana* L. (Pokeweed), *Poaceae* spp. L. (Grasses) |
| L2 | 35 | 40 | 25 | 0 | *C. angustifolium*, *Chamaecrista nictitans* Moench (Sensitive Partridge Pea), *Eupatorium capillifolium* Small (Dogfennel) |
| L3 | 60 | 5 | 10 | 25 | *P. americana* |
| L4 | 50 | 0 | 0 | 50 | *P. americana* |
| L5 | 60 | 15 | 0 | 25 | *P. americana*, *C. angustifolium*, *Ailanthus altissima* Swingle (Tree of Heaven) |
| M1 | 15 | 30 | 40 | 15 | *Panicum virgatum* L. (Switchgrass), *Populus alba* L. (White Poplar), *Smilax rotundifolia* L. (Common Greenbrier) |
| M2 | 15 | 35 | 35 | 15 | *P. virgatum, Poaceae* spp., *P. alba* |
| M3 | 10 | 40 | 40 | 10 | *P. virgatum, Gaylussacia baccata* Koch (Black Huckleberry), *Eupatorium rotundifolium* L. (Roundleaf Thoroughwort) |
| M4 | 0 | 70 | 10 | 20 | *G. baccata, Poaceae* spp. |
| M5 | 20 | 15 | 40 | 25 | P. *virgatum, E. capillifolium, Rubus cuneifolius* Pursh (Sand Blackberry) |
| H1 | 0 | 50 | 0 | 50 | *Clethra alnifolia* L. (Summersweet) |
| H2 | 0 | 5 | 0 | 95 | *Ilex opaca* Aiton (American Holly) |
| H3 | 5 | 0 | 45 | 50 | *Poaceae* spp. |
| H4 | 1 | 10 | 5 | 84 | *G. baccata* *Poaceae* spp. |
| H5 | 0 | 25 | 0 | 75 | *G. baccata* |

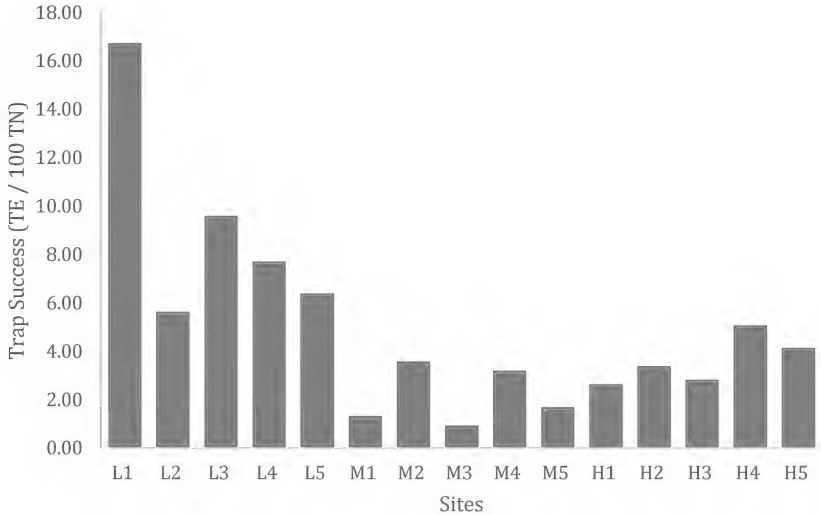



**FIGURE S1**. Trap success pooled across species at each camera trap site in low (L), medium (M), and high (H) basal areas at Fort A.P. Hill, VA.

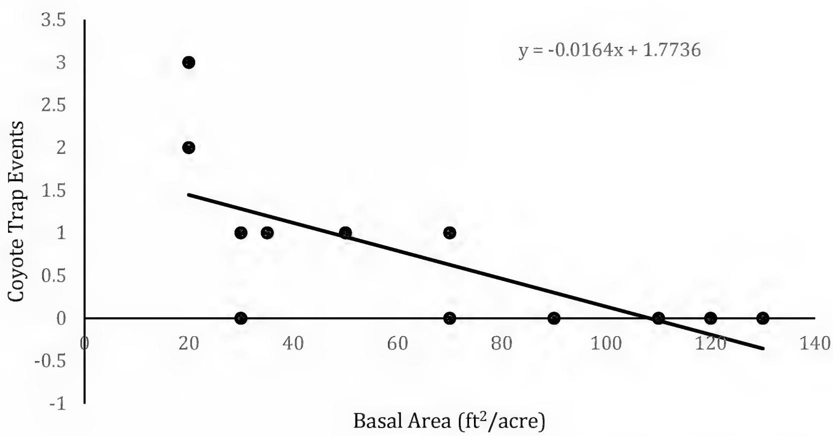



**FIGURE S2**. Coyote presence by basal area ($R^2$ = 0.51, F(1,13) = 13.43, p = 0.003). Number of Coyote trap events captured by cameras located in varying basal areas (20-130 $ft^2$/acre). 15 total camera trap sites.

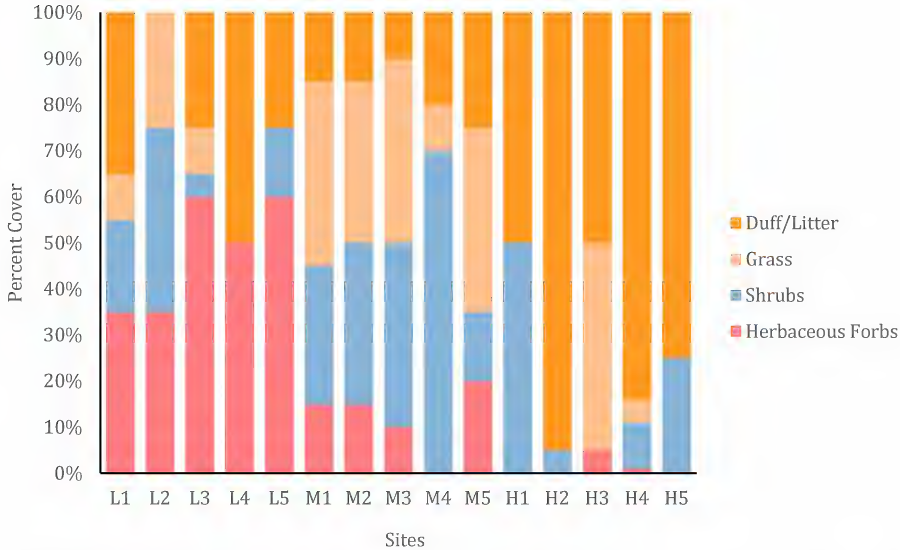



**FIGURE S3**. Percent of cover of vegetation types at ground level, including, herbaceous forbs, shrubs, grasses, and duff/litter at each camera trap site in low (L), medium (M), and high (H) basal areas at Fort A.P. Hill, VA

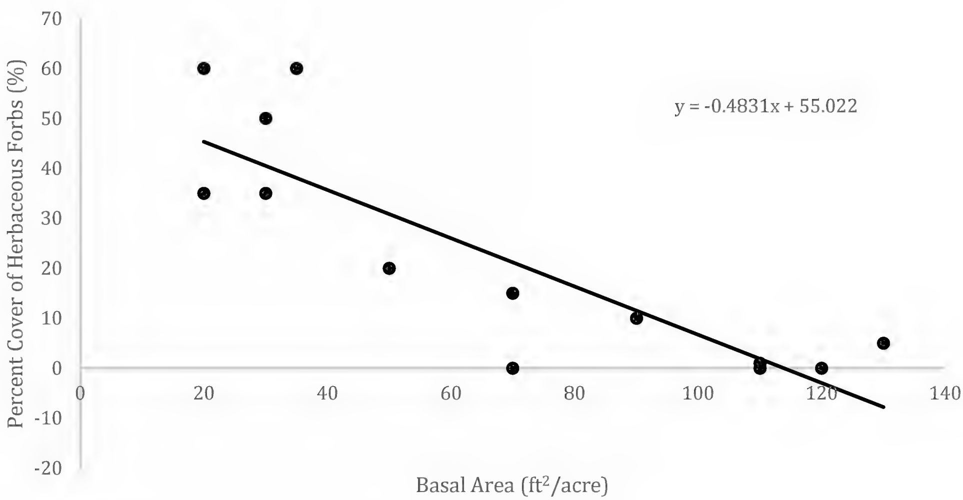



**FIGURE S4**. Plot of percent cover of herbaceous forbs across the various basal areas found at each camera trap site with trendline. Herbaceous forbs and basal area Pearson's correlation r (13) = -0.86, p = 0.000033).

**Virginia Journal of Science** / Volume 72, Issue 3 & 4 / Fall & Winter 2021
doi: 10.25778/yq9h-nx52

# Remote Detection of Disturbance from Motorized Vehicle Use in Appalachian Wetlands

Walter H. Smith

Department of Natural Sciences, The University of Virginia's College at Wise
Wise, Virginia 24293 (whs2q@uvawise.edu)

## ABSTRACT

Wetland disturbance from motorized vehicle use is a growing concern across the Appalachian coalfields of southwestern Virginia and portions of adjacent states, particularly as both extractive industries and outdoor recreation development expand in regional communities. However, few attempts have been made in this region or elsewhere to adapt approaches that can assist researchers and land managers in remotely identifying and monitoring wetland habitats disturbed by motorized vehicle use. A comparative analysis of wetlands impacted and unimpacted by off-road vehicle activity at a public recreation area in Tazewell County, Virginia was conducted to determine if and how a common, satellite-derived index of vegetation health, normalized difference vegetation index (NDVI), can remotely detect wetland disturbance. NDVI values were consistently lower in wetlands impacted by several years of off-road vehicle use when compared to adjacent, unimpacted sites, with statistically-significant NDVI coldspots growing in size in impacted wetlands across the same time period. While considerations exist related to the resolution of data sources and the identification of specific modes of disturbance, NDVI and associated spatial analysis tools may provide a simple and cost-effective way for researchers and land managers to remotely monitor rates of wetland disturbance across mountainous portions of the eastern United States.

**Key Words:** NDVI, vegetation, off-road vehicle, disturbance, wetland

## INTRODUCTION

The coalfields of the central Appalachian Mountains, located across southwestern Virginia, eastern Kentucky, southern West Virginia, and eastern Tennessee, have historically been one of

the most heavily-impacted areas of the eastern United States in terms of anthropogenic disturbances. More than 3000 $km^2$ of this region have been altered due to surface mineral extraction, with extensive timber harvesting and gas well development occurring across the same region (Saylor 2008; Townsend et al. 2009; Miller and Zegre 2016; Ross et al. 2016). Past work has found these activities to exert significant ecological pressures on ecosystems across the Appalachian coalfields, including reduced habitat availability and altered community composition for bird, herpetofauna, and plant taxa, as well as changes to water quality and nutrient cycling in regional waterways (Petty et al. 2013; Wickham et al. 2013; Maigret et al. 2019).

Wetland ecosystems are of particular concern within the central Appalachian coalfields. The overall extent and number of wetland habitats is lower in this region compared to other Appalachian physiographic provinces due to steep terrain that constrains wetland formation mostly to floodplain areas along rivers and larger streams, as well as midslope seepages near the headwaters of smaller streams (Thompson et al. 2007; Fleming and Patterson 2017). As a result, wetlands in this region are typically given a high conservation value and are a management priority within regional protected areas (USDA Forest Service 2004; Thompson et al. 2012; Weber and Bulluck 2014).

Wetlands and waterways across the central Appalachian region have faced disturbance risks from the aforementioned forms of natural resource extraction, including altered water chemistry and quality (Kiviat 2013; Cook et al. 2015), altered soil dynamics (Stephens et al. 2015), and the introduction of non-native taxa into wetland vegetation assemblages (Balcombe et al. 2005). However, ongoing socioeconomic shifts across the region are resulting in a decrease in surface mining and related forms of disturbance and a corresponding increase in recreational development across large parcels of private and public land formerly used for resource extraction (Frisch and Johanssen 2014; Scott et al. 2017). In particular, the development of off-road vehicle trail systems is a growing economic development strategy being employed by local and state governments, with more than 1500 km of motorized trails developed across southwestern Virginia, southern West Virginia, eastern Kentucky, and eastern Tennessee (Hackbert and Lin 2009; Scott 2010).

Wetland ecosystems worldwide are often targeted for motorized trail development or otherwise impacted by off-road use (Meyer 2002; Arp and Simmons 2012). These activities have been shown in past work to decrease vegetation biomass and productivity in some wetland habitats (Hannaford and Resh 1999; Welch et al. 2002) and alter the composition of some wetland vegetation assemblages (Taylor and Raney 2013). Soil compaction from off-road vehicle use is also of particular concern across multiple habitat types since it can lead to diminished moisture infiltration needed to support plant growth, as well as increased rates of soil erosion (Webb and Wilshire 1983; Liddle 1997; Ouren et al. 2009). Impacts from soil compaction generally increase with the number of vehicle passes at a given site (Iverson et al. 1981; Lovich and Bainbridge 1999), with soil compaction from vehicle use persisting for years following disturbance in some habitat types (Ahlstrand and Racine 1993). Wetlands also exhibit some of the highest susceptibility to trail-related erosion and soil scouring when compared to dry forested sites and other terrestrial habitats (Sobczak and Pernas 2002; Trip and Wiersma 2015). These impacts have cumulatively led many trail planning programs to recommend wetland avoidance during motorized trail

development to minimize environmental impacts (Snyder et al. 2008). In spite of these concerns, few attempts have been made to gauge the extent of wetland disturbance and other environmental impacts due to motorized trail development across the central Appalachian region, where trail networks are expanding at an increasing rate (Sharp et al. 2020). This lack of an ability to detect and monitor wetland disturbance from off-road vehicle use at the landscape scale currently precludes such assessments, as well as the development of studies examining the ecological impacts of such activities and the design of appropriate mitigation measures.

Remote sensing approaches hold promise as one avenue for both researchers and land managers to identify wetlands damaged by off-road vehicle use and other anthropogenic disturbances. Remotely-sensed imagery, for example, can both highlight the location of wetland habitats within the surrounding landscape matrix (Ozesmi and Bauer 2002; Adam et al. 2010) and identify spatiotemporal changes in wetland characteristics using indices of ecological condition derived from remotely-sensed data (Mayer and Lopez 2011; Hinkel et al. 2017). Such remote sensing approaches and associated metrics have been used to detect signatures of both natural (Rodgers et al. 2009; Potter 2018) and anthropogenic (Kayastha et al. 2012; Alatorre et al. 2016; Jaramillo et al. 2018) disturbances in wetland habitats across a variety of ecosystems. In particular, normalized vegetation difference index (NDVI) data are increasingly being incorporated as a metric of vegetation health that can allow researchers to remotely gauge wetland condition in response to disturbance events (Potter 2018; Wilson and Norman 2018; Taddeo et al. 2019; Vanderhoof et al. 2020). To date, however, these approaches have yet to become adapted for use in detecting signatures of wetland disturbance from motorized vehicle use. The purpose of this study was therefore to test the ability of remotely-sensed datasets to identify wetland disturbance in response to motorized vehicle use, particularly for wetlands impacted by vegetation loss and vehicle scouring, at a site heavily impacted by off-road vehicle trail development in the New River watershed of southwestern Virginia.

## MATERIALS AND METHODS

### Study Area

The focal area of this study encompassed a 20 $km^2$ region along the northern half of the lower Laurel Fork watershed in Tazewell County, Virginia, specifically an area presently maintained as a public off-road vehicle recreation area by Virginia's Southwest Regional Recreation Authority. Habitats across this area are mixed mesophytic forest ecosystems typical of middle and lower elevations within the Cumberland Mountains Physiographic Province, with past surface mining activities originating during the 1970s occurring across portions of the region. Wetlands across the study area are primarily large headwater seepage wetlands, isolated wetlands incidentally formed as a result of past surface mining, and floodplain wetlands along larger streams.

Six wetland areas from the study area were selected for analysis: three wetland areas that have been incorporated as water features along official motorized trails (hereafter "impacted" wetlands) and three wetland areas not associated with (e.g., >0.25 km from) official motorized routes (hereafter "unimpacted" wetlands; Fig. 1). All selected sites were open-canopy wetlands

characterized predominantly by emergent vegetation occurring within flat to gently-sloping zones of groundwater discharge along first- or second-order headwater streams. Small and shallow headwater wetlands of this type are common across the Cumberland Mountains where either naturally-occurring terrain or terrain modified by surface mining activities facilitates the pooling of surface runoff and groundwater discharge and the establishment of wetland soils and vegetation (Thompson et al. 2007; Atkinson et al. 2010). All wetlands were of roughly equivalent size (0.5-2.14 ha) and at roughly equivalent elevations (760-790 m asl), and none have experienced any significant anthropogenic disturbance, outside of the off-road vehicle use being investigated in this study, in at least the past five years. Off-road vehicle disturbance was confirmed at all impacted sites via evidence of substantial vehicle scouring (tire rutting of wetland soils, crushed vegetation) along with official trail signage within each wetland area during field visits following the peak recreation season in late September of 2018 and 2019.

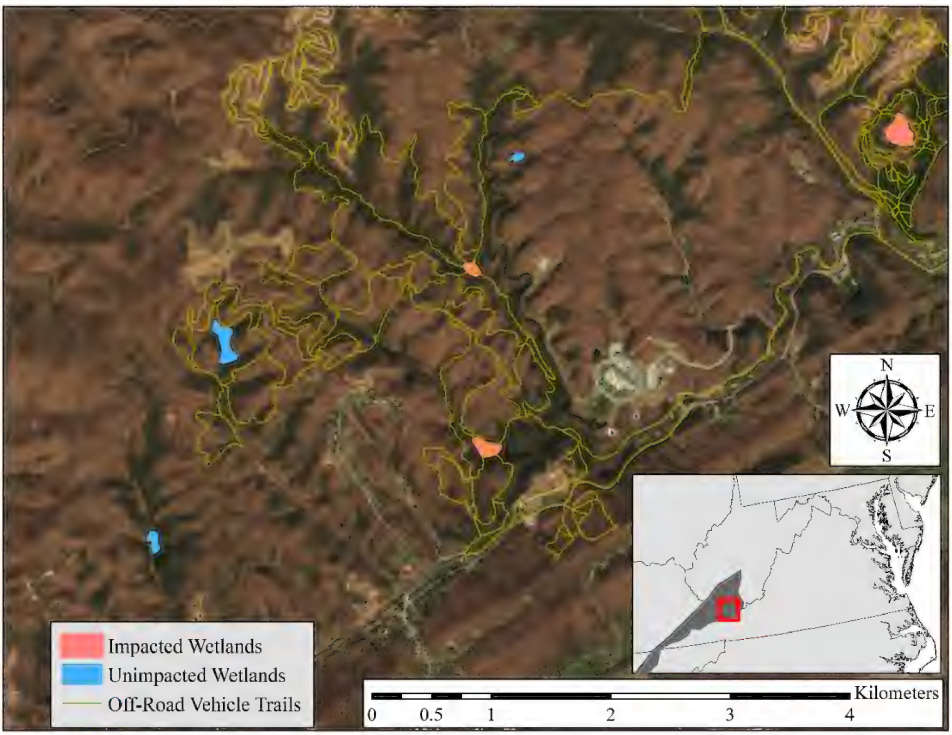



**FIGURE 1**: Focal wetlands at the Original Pocahontas Off-Road Vehicle Trail System in Tazewell County, Virginia. Trail locations were generated from publicly-available GPS data from the trail system's managing agency (http://spearheadtrails.com). Red box in inset map denotes location of the study area, with the shaded region denoting the location of the Cumberland Mountains province along the borders of Virginia, Tennessee, Kentucky, and West Virginia, where rapid off-road vehicle trail development is occurring at the regional scale.

Data Sources

Wetlands impacted by off-road vehicles should exhibit significant differences in remotely-sensed indices of vegetation health, relative to unimpacted wetlands across the same area. To test this, 100 x 100 $km^2$ tiles from publicly-available Sentinel-2 satellite imagery were downloaded. Sentinel-2 imagery is generated across 13 spectral bands that include visible, near infrared, and short-wave infrared spectra at a spatial resolution of 10 m to 60 m (Drusch et al. 2012). Sentinel-2 tiles were downloaded from the United States Geological Survey Earth Resources Observation and Science Center (https://www.usgs.gov/centers/eros).

Specifically, a representative Sentinel-2 tile was chosen covering the study area from each year encompassing a timespan from 2015-2019, corresponding to dates before the full study area's opening to off-road users (2015) and multiple years of imagery following its opening date (2016-2019). An imagery date for each year was selected from the same period within the local dry season (the final two weeks of October) in order to (i) capture wetland condition following the peak summer recreation season and (ii) minimize confounding seasonal differences in vegetation growth, precipitation, and artifacts from standing water. All imagery was additionally recorded prior to the local onset of colder temperatures and significant frost events. Imagery was also selected to minimize cloud cover, with no cloud cover visible across the study area in any of the aforementioned images.

Multispectral bands from Sentinel-2 imagery can be used to calculate indices of ecological condition, specifically those reflecting vegetation health. Sentinel-2 imagery was used to calculate one such index, normalized difference vegetation index (NDVI), which summarizes vegetation health on a 1 to -1 scale (Goward et al. 1991). NDVI was calculated for each year (2015-2019) using the Image Analysis extension in ArcGIS v10.3 as the following:

$$NDVI = \frac{(IR - R)}{(IR + R)}$$

where IR and R refer to pixel values from the 10 m infrared and red Sentinel-2 bands, respectively. Following NDVI calculation, NDVI pixel values were extracted for each year from within each focal wetland for further analysis. Wetland polygons were generated based on wetland extents as identified by the Virginia Wetlands Catalog (Weber and Bulluck 2014) and high-resolution aerial orthoimagery (VGIN 2019).

Statistical Analyses

NDVI data from successive dates can be used to quantify vegetation change across a time series (Piao et al. 2006; Franke and Menz 2007; Zhao et al. 2009). Linear Mixed Effects Models were used to evaluate relationships between NDVI, wetland type (impacted vs. unimpacted), and year, with NDVI as a dependent variable and wetland type and year included as independent variables. Models were constructed using the lmer function in the lme4 package in R.

Specifically, four candidate models were evaluated reflecting the following potential explanatory variables for NDVI patterns as fixed factors: wetland type alone, year alone, an interaction between wetland type and year, and a null model with no fixed factors. Since pixels from the same wetland sites were not independent, site was included as a random factor in all candidate models. Models were evaluated using Akaike's Information Criterion (AIC) via the anova function in the car package in R, with pairwise comparisons between interaction terms (wetland types per year) performed using the emmeans package.

A more informative measure of vegetation change than aggregated decreases in NDVI is that of spatial clustering of low NDVI values. Specifically, statistically-significant clusters of NDVI minima would be expected to be present in wetland areas experiencing disturbance from off-road vehicles, with the size of such clustered minima expanding over time as disturbance continues. The Getis-Ord Gi* statistic (Getis and Ord 1992) was used to assess statistically significant patterns of clustering of high and low NDVI values – or hotspots and coldspots, respectively – across the study area. The Getis-Ord Gi* statistic compares grid cell values to those of neighboring features, assessing the significance of clustered patterns by comparing actual local sums to expected local sums from the same areas. Resulting values can then be grouped into bins representing the degree of statistically-significant clustering across a spatial extent.

Getis-Ord Gi* statistics were calculated for each year's NDVI dataset using the Hot Spot Analysis function in ArcGIS v10.3. Resulting hotspots and coldspots (99% confidence, 95% confidence, and nonsignificant clustering) were visually identified in ArcGIS, with Getis-Ord Gi* statistics exported for each year within each focal wetland polygon.

## RESULTS

Linear mixed effects models indicated that wetland type, year, and an interaction between these two factors were all significant ($\alpha = 0.05$) predictors of NDVI, with the full model (wetland type + year + wetland type x year) being the best model based on AIC values (Table 1). Mean NDVI values were not significantly different between impacted and unimpacted wetlands in 2015 (prior to the full trail system's opening and the onset of vehicle disturbance at impacted sites) or in 2016 (early in the study area's operation as a motorized recreation area); however, mean NDVI values were significantly lower in impacted wetlands when compared to unimpacted wetlands in each year from 2017-2019, following multiple years of motorized use in impacted wetlands (Fig. 2). Differences between impacted and unimpacted wetland types generally increased in the years following the opening of the trail system to motorized users and an increase in vehicle disturbance, with NDVI differences between impacted and unimpacted wetlands more than doubling between 2015 and 2018 (Fig. 3). These patterns match with actual conditions at each impacted site, which contained large and growing areas of crushed vegetation and scoured/compacted soil in wheel ruts (see aerial orthoimagery in Fig. 4), versus unimpacted wetlands lacking these features.

Impacted wetlands were also characterized by significant NDVI coldspots determined via hotspot analyses in ArcGIS v10.3. The proportion of each impacted wetland characterized by statistically-significant clustering of low NDVI values generally increased after the study area was opened to motorized users (Fig. 4), with the size of coldspots within wetland polygons more than

doubling from 2015 to 2019 at impacted sites (Table 2). Nearby unimpacted wetlands generally exhibited a lack of increasing coldspot formation, with the proportion of each wetland characterized by statistically-significant clustering of low NDVI values remaining relatively constant from 2015-2019. By contrast, several unimpacted wetlands exhibited increasing levels of hotspot formation, indicating significant clustering of high NDVI values and an improvement in vegetation health.

**TABLE 1**: Linear mixed effects model results for four candidate models explaining NDVI variability in wetlands across the lower Laurel Fork watershed on Virginia's Original Pocahontas Off-Road Trail System. For listed candidate models, "None" refers to the model including no predictor variables, "Type" refers to the model including wetland type (impacted versus unimpacted) only, "Year" refers to the year of imagery only, and "Type*Year" refers to an interaction between year and wetland type. "npar" refers to the number of parameters, "AIC" refers to Akaike's Information Criterion, and "logLik" refers to the log-likelihood value.

| Model | npar | AIC | logLik | Wald $\chi^2$ | P-value |
|---|---|---|---|---|---|
| Type*Year | 5 | 14146 | -7068.0 | 5.0978 | 0.02 |
| Year | 4 | 14149 | -7070.6 | 15.1867 | <0.0001 |
| Type | 4 | 14164 | -7078.2 | 5.0992 | 0.02 |
| None | 3 | 14167 | -7080.7 | n.a. | n.a. |

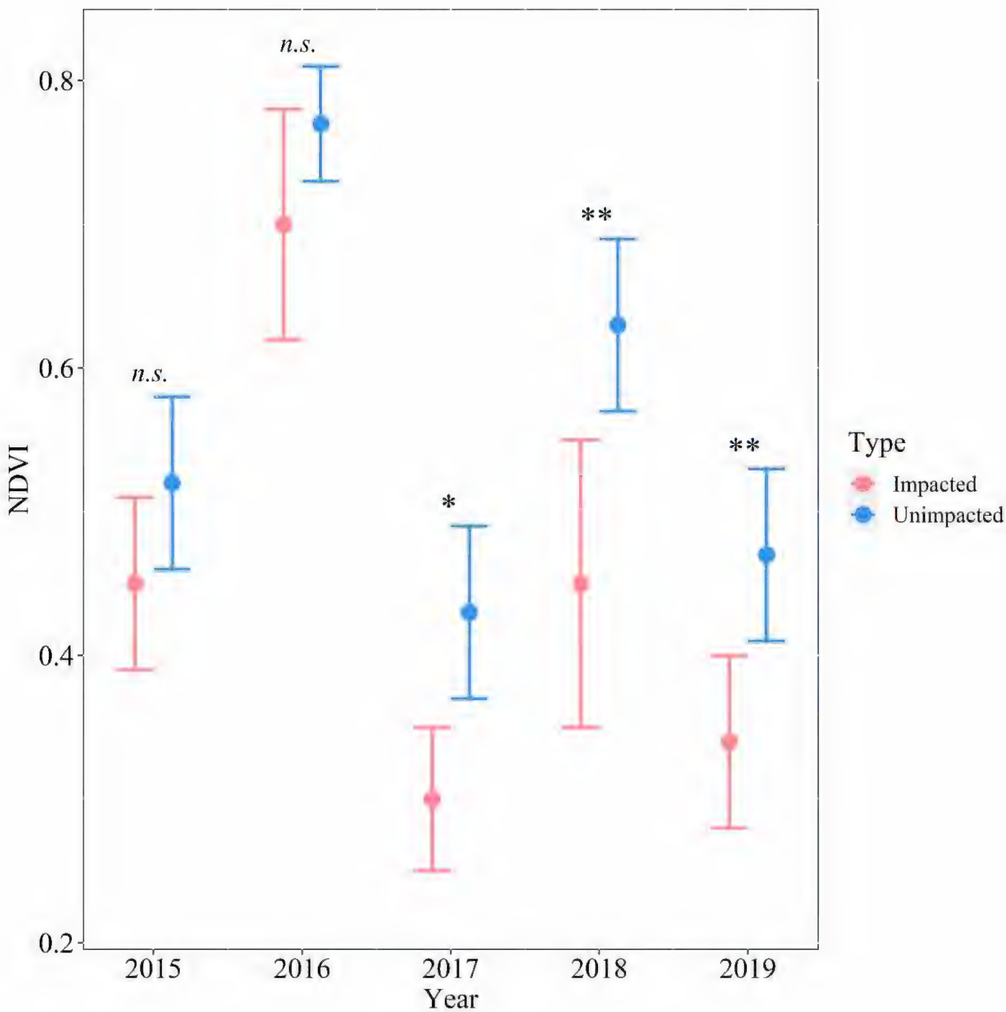



**FIGURE 2**: Comparison of annual NDVI values (mean ± 1 SD) across impacted and unimpacted wetlands at the Original Pocahontas Off-Road Vehicle Trail System in Tazewell County, Virginia. Labels denote significance levels of comparisons between impacted and unimpacted wetlands within each respective year (n.s. = non-significant; * = $P < 0.05$; ** = $P < 0.01$).

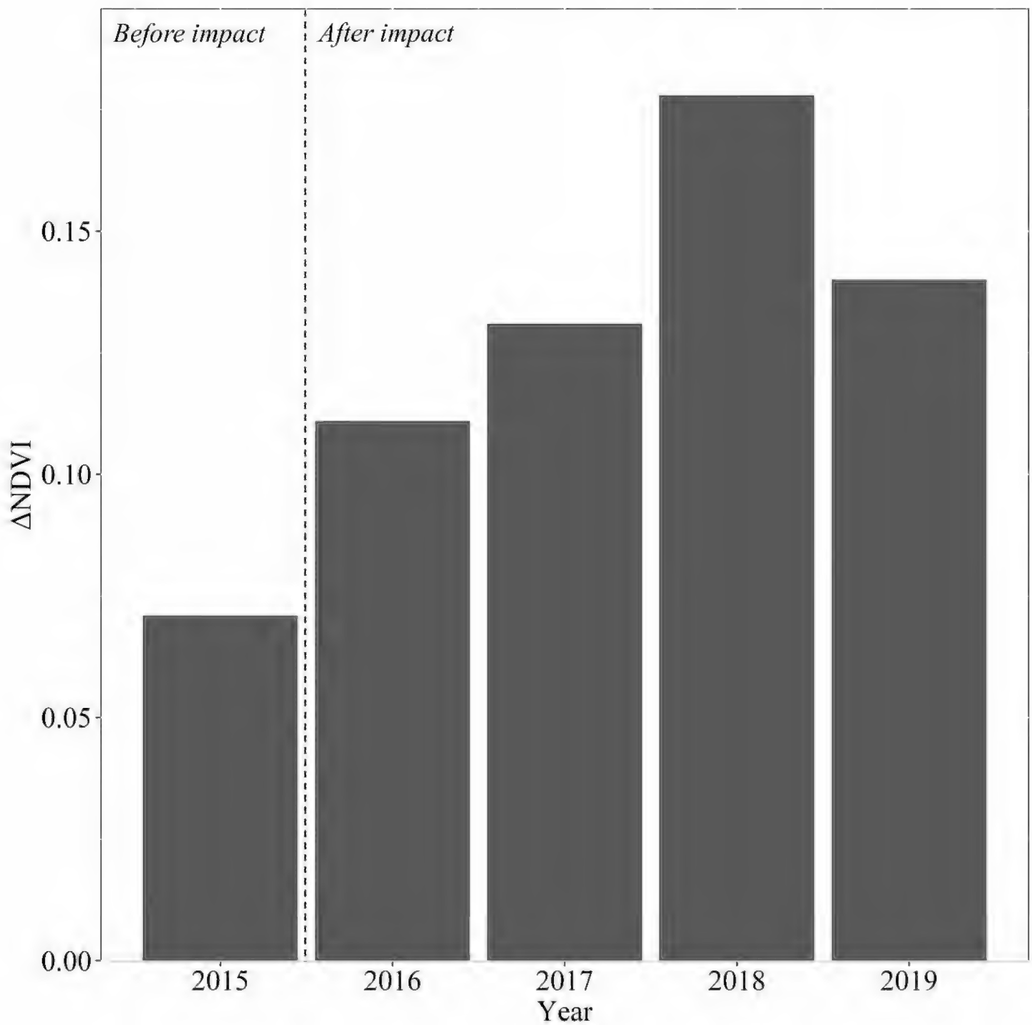
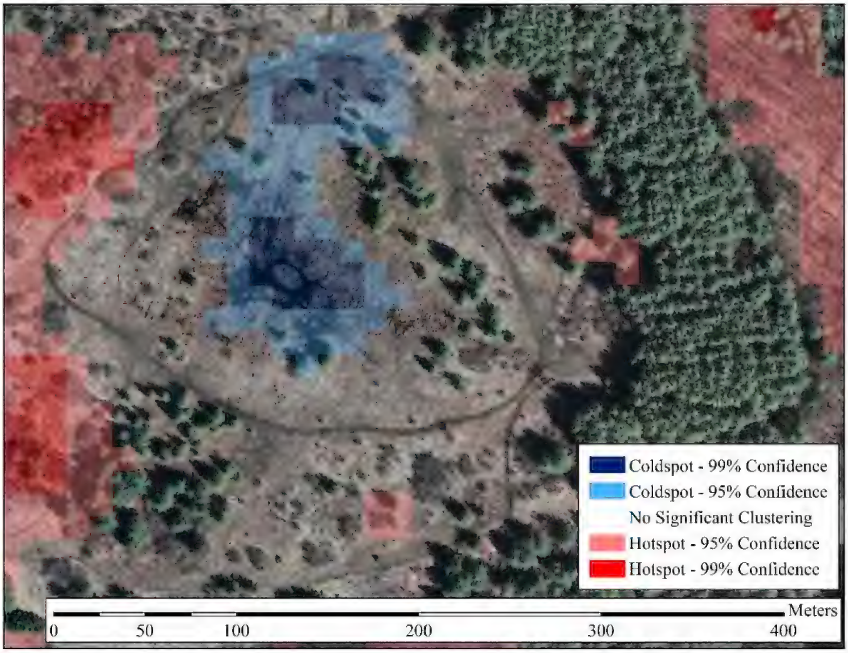



**FIGURE 3**: Differences in mean NDVI (ΔNDVI) between wetlands impacted by off-road vehicle disturbance and those unimpacted by off-road vehicle disturbance at Virginia's Original Pocahontas Trail System per year from 2015-2019. 2015 represents the year prior to the full study area's opening to motorized users; impacted wetlands were open to motorized vehicle use in each successive year.

(Fig. 4, A)


Coldspot - 99% Confidence
Coldspot - 95% Confidence
No Significant Clustering
Hotspot - 95% Confidence
Hotspot - 99% Confidence
Meters
0 50 100 200 300 400

(Fig. 4, B)

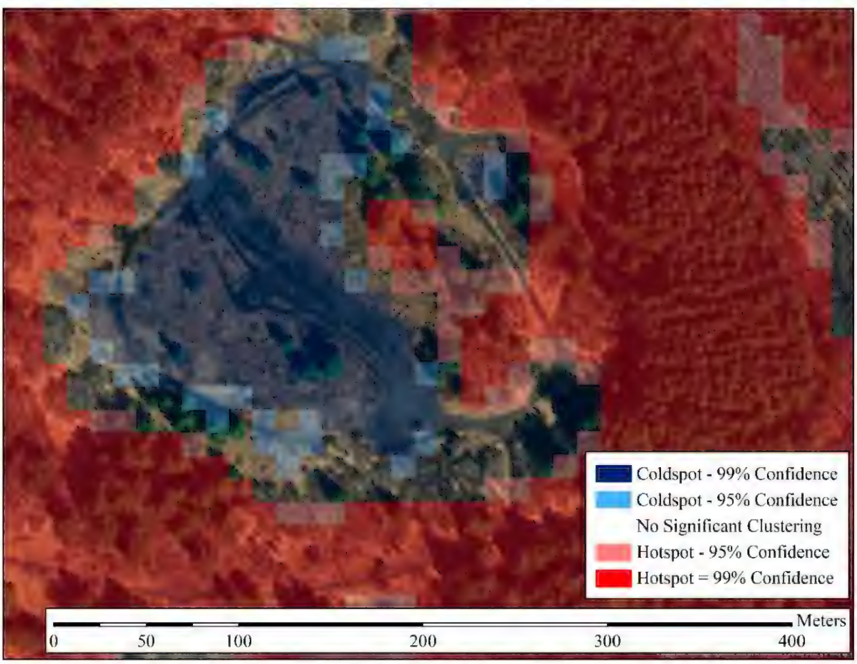

Coldspot - 99% Confidence
Coldspot - 95% Confidence
No Significant Clustering
Hotspot - 95% Confidence
Hotspot = 99% Confidence
Meters
0 50 100 200 300 400

**FIGURE 4:** Representative example of NDVI coldspot formation over time at a single wetland site impacted by off-road vehicle trails (Trail 10) in Tazewell County, Virginia: (A) wetland prior to the trail system's opening, and (B) the same wetland in 2019 after multiple years of being open to off-road vehicle use. Note substantial scouring of vegetation and underlying soils in tire tracks from vehicle travel accompanying separate NDVI coldspot in 2019.
(Fig. 4, B)

**TABLE 2**: Proportion of wetland areas at the Original Pocahontas Off-Road Vehicle Trail System comprised of statistically-significant NDVI coldspots per year. "Impacted" denotes wetlands co-located with official off-road vehicle routes and exhibiting signs of vehicle disturbance (tire rutting, vegetation scouring), while "unimpacted" denotes wetlands not co-located with official vehicle routes. 2015 denotes the year prior to the onset of wetland impacts, with impacted wetlands open to vehicle use in each successive year. Asterisk denotes one year's imagery that resulted in inflated NDVI values across the entire Sentinel-2 tile; see text for discussion of this outlier.

| Wetland | Type | 2015 | 2016* | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|
| Trail 10 | Impacted | 0.33 | 0.32 | 0.53 | 0.95 | 0.87 |
| Trail 80 | Impacted | 0.62 | 0 | 0.67 | 0.89 | 0.73 |
| Trail 90 | Impacted | 0.23 | 0 | 0.2 | 0.68 | 0.46 |
| Curran Branch | Unimpacted | 0.08 | 0 | 0 | 0 | 0.01 |
| Farmers Branch | Unimpacted | 0.1 | 0 | 0.09 | 0.24 | 0.11 |
| Haynes Branch | Unimpacted | 0.08 | 0 | 0 | 0.26 | 0.02 |

## DISCUSSION

Remotely-sensed indices of ecological condition are commonly used to assess spatiotemporal changes in the condition of wetlands and other habitat types (Pettorelli et al. 2005). In particular, NDVI and associated metrics have been found to serve as an indicator of wetland condition that can highlight signatures from a variety of wetland disturbances, including severe storm events (Rodgers et al. 2009), commercial development and agricultural practices (Kayastha et al. 2012; Alatorre et al. 2016), short-term spill events involving chemical pollutants (Jaramillo et al. 2018), and wildfires (Potter 2018). The results of this study suggest that these same indices are also capable of detecting patterns of anthropogenic disturbance in wetlands targeted for motorized vehicle trail development in mountainous terrain. One strength of this study was being able to statistically compare remotely-sensed indices across wetlands whose disturbance histories were known, clarifying signatures associated with wetland disturbance that may be beneficial for land managers and others seeking to gauge the extent of wetland disturbance in other areas.

In particular, a common index of vegetation health (NDVI) showed significant differences between impacted and unimpacted wetlands, with differences in NDVI values increasing across wetland types over time after the study area was opened to the public as a motorized recreation area. One interesting pattern apparent in this dataset was that NDVI values across all sites increased in 2016 relative to other years, regardless of disturbance history. This pattern was consistent across the entire Sentinel 2 tile used to render NDVI data, even at sites characterized by unvegetated and impervious surfaces. Why this particular pattern occurred for 2016 is unclear, although this may be due to artifacts from high cloud contamination or other atmospheric effects (Eklundh 1995; Ali et al. 2013). However, the general patterns of significance and model support for the NDVI comparisons reported above were unchanged when evaluating models with data from this year excluded as a potential outlier.

Lower NDVI values in wetlands impacted by off-road vehicle use would be expected, since past research has shown that such development can have detrimental impacts on wetland habitats. Both wetland vegetation and the soils necessary for the establishment of wetland plant assemblages, for example, can be negatively impacted by persistent off-road vehicle use (Hannaford and Resh 1999; Trip and Wiersma 2015), with soil damage potentially persisting for years following an initial disturbance event (Ahlstrand and Racine 1993). Vehicle scouring of the type observed across the study area during field visits should therefore be expected to remove emergent vegetation cover and replace it with open substrate, leading to a decrease in NDVI values relative to nearby unimpacted wetlands, whose vegetation assemblages have not been physically disturbed. Indeed, past work with both natural and anthropogenic wetland disturbance has found similar signatures of decreasing NDVI values during and following disturbance events (Potter 2018; Wilson and Norman 2018; Taddeo et al. 2019; Vanderhoof et al. 2020).

Most importantly, NDVI values not only decreased within impacted wetlands but showed increasing patterns of statistically-significant coldspot development over time, highlighting the clustering of low NDVI values. Such clustered values are valuable since they reflect spatially-coherent patterns of NDVI maxima or minima, rather than scattered noise reflecting extreme NDVI values in single pixels or grid cells (Boschetti et al. 2013; Chakraborty et al. 2018). The observed trend of coldspots increasing in size in impacted wetlands over time is consistent with increasing wetland disturbance from persistent off-road vehicle use, especially when coupled with a relative lack of statistically-significant coldspots in adjacent unimpacted wetland habitats. In fact, Getis-Ord analyses indicated that these unimpacted wetlands actually exhibited even some NDVI hotspot development in several cases, indicating an increase in vegetation health at the same time nearby impacted wetlands were experiencing growing clusters of NDVI minima.

These results suggest that NDVI data may be particularly useful for researchers and land managers charged with assessing the extent of wetland disturbance as a result of motorized vehicle use. In particular, the consistent or growing presence of statistically-significant clusters of NDVI minima within wetlands across a time series appears to be strongly indicative of vegetation loss associated with wetland disturbance. Since satellite data producing spectra required for the calculation of NDVI are freely and publicly available from a variety of sources, the approach outlined in this study may be especially useful in cases where other remotely-sensed data sources,

such LiDAR coverage and high-resolution orthoimagery, are unavailable to assist in the landscape-scale detection of wetland change.

However, there are several important limitations to the approach outlined in this study. First, researchers should use caution when ascribing differences in NDVI values to specific forms of disturbance, such as the off-road vehicle use investigated in this study, when the disturbance histories of wetland sites are not known *a priori*. For example, temporal changes in NDVI are not solely caused by anthropogenic disturbances but may also reflect natural disturbance events, stressors such as drought or disease, and changes in vegetation assemblages resulting from ecological succession (Piao et al. 2006; Franke and Menz 2007; Zhao et al. 2009). The NDVI differences outlined in this study were strongly indicative of anthropogenic disturbance from motorized vehicles due to (i) the known disturbance histories of the wetlands selected for study, and (ii) the ability to statistically compare wetlands impacted by motorized vehicle use and those unimpacted by these and other disturbances across the same spatial extent and time period. However, other areas where this approach is applied may not have the luxury of pre-existing knowledge about the recent disturbance histories or condition of focal wetlands, meaning that trends in NDVI minima should not be viewed as a sole indicator of anthropogenic disturbance. Instead, these data are likely best suited as an initial step in screening wetlands for putative disturbance events, with follow-up comparisons via high-resolution aerial orthoimagery and/or field assessments necessary to fully gauge such impacts.

Second, this study was restricted to primarily open-canopy wetlands not located beneath thick forest cover. While most wetlands located in mid- or upslope positions in the study region possess such structural attributes, particularly for wetlands formed on former surface mines (Thompson et al. 2007; Atkinson et al. 2010), floodplain and riparian wetlands located along rivers and other large waterways may not share these characteristics and may be located in closed-canopy situations. These wetland types were not present in the immediate study area, and it remains unknown if and how the presence of a dense forest canopy may impact NDVI values in cases where disturbance activities impact wetland vegetation closer to the ground layer and do not result in the removal of overstory vegetation. NDVI data from all habitats may also be seasonally variable in response to senescence late in the growing season, dormant vegetation outside of the growing season, and increasing greenness during spring months (Zoffoli et al. 2008; Lumbierres et al. 2017; Xu et al. 2017), potentially confounding NDVI-based assessments of wetland condition if comparisons of a collection of sites are made using imagery from widely differing dates or seasons. Assessing these impacts may be one potential area for future study.

The detection of changes in NDVI data following disturbance events is also likely dependent on the resolution of the satellite datasets used to calculate NDVI and related indices. The Sentinel-2 data used here are among the most high-resolution (10 m) multispectral data publicly available. While these data appear to be able to effectively detect wetland change within the study region, more high-resolution datasets do exist from proprietary sources and may be able to more effectively detect wetland change due to various forms of anthropogenic disturbance. Similarly, more coarse-resolution data from publicly-available data sources such as the Moderate Resolution Imaging Spectroradiometer (MODIS; Ardanuy et al. 1991) and Advanced Very High Resolution Radiometer (AVHRR; Holben 1986) may be less capable of detecting change in

wetlands of the size used in this study, making the source of remotely-sensed data a critical consideration for others seeking to adapt this study's approach.

In conclusion, NDVI data can be a useful tool for detecting signatures of disturbance from motorized vehicle use in open-canopy wetland habitats, particularly when coupled with statistical approaches designed to detect spatially-coherent patterns of NDVI gain or loss. The results of this study underscore the ability for NDVI data to detect small-scale disturbances in wetlands, adding to a growing list of disturbances from both natural and anthropogenic sources that are detectable in wetlands using NDVI data. The off-road vehicle use and associated habitat disturbances investigated in this study are growing in scope and intensity across the central Appalachians and are presently considered one of the predominant forms of landscape change and associated conservation threats for some aquatic taxa across this region (USFWS 2016). However, little to no information currently exists on the regional extent of such disturbances in wetland ecosystems. As research into the extent of such disturbances, their ecological impacts, and potential mitigation measures increases both within the central Appalachian region and beyond, these remote sensing approaches may form a key tool alongside traditional field-based habitat assessments.

## ACKNOWLEDGMENTS

I am grateful to P. Shelton, W. Browning, M. Bell, H. Warren, and D. Withen for their valuable help in conceptual discussions surrounding the questions addressed in this manuscript. Site access for field assessments for this project was performed under User Permit 6613 for the Southwest Regional Recreation Area.

## LITERATURE CITED

Adam, E., O. Mutanga, and D. Rugege. 2010. Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: A review. Wetlands Ecology and Management 18:281-296. https://doi.org/10.1007/s11273-009-9169-z

Ahlstrand, G. M., and C. H. Racine. 1993. Response of an Alaska, USA, shrub-tussock community to selected all-terrain vehicle use. Arctic and Alpine Research 25: 142–149. https://doi.org/10.1080/00040851.1993.12002995

Alatorre, L. C., S. Sanchez-Carrillo, S. Miramontes-Beltran, R. J. Medina, M. E. Torres-Olave, L. C. Bravo, L. C. Wiebe, A. Granados, D. K. Adams, E. Sanchez, and M. Uc. 2016. Temporal changes of NDVI for qualitative environmental assessment of mangroves: Shrimp farming impact on the health decline of the arid mangroves in the Gulf of California (1990–2010). Journal of Arid Environments 125:98-109. https://doi.org/10.1016/j.jaridenv.2015.10.010

Ali, A., K. de Bie, and A. K. Skidmore. 2013. Detecting long-duration cloud contamination in hyper-temporal NDVI imagery. International Journal of Applied Earth Observation and Geoinformation 24:22-31. https://doi.org/10.1016/j.jag.2013.02.001

Ardanuy, P. E., D. Han, and V. V. Salomonson. 1991. The Moderate Resolution Imaging Spectrometer (MODIS) science and data system requirements. IEEE Transactions on Geoscience and Remote Sensing 29:75-88. http://dx.doi.org/10.1109/36.103295

Arp, C. D., and T. Simmons. 2012. Analyzing the impacts of off-road vehicle (ORV) trails on watershed processes in Wrangell-St. Elias National Park and Preserve, Alaska. Environmental Management, 49:751–766. https://doi.org/10.1007/s00267-012-9811-z

Atkinson, R. B., J. E. Perry, G. B. Noe, W. L. Daniels, and J. Cairns, Jr. 2010. Primary productivity in 20-year old created wetlands in Southwestern Virginia. Wetlands 30:200-210. https://doi.org/10.1007/s13157-010-0033-y

Balcombe, C. K., J. T. Anderson, R. H. Fortney, J. S. Rentch, W. N. Grafton, and W. S. Kordek. 2005. A comparison of plant communities in mitigation and reference wetlands in the mid-Appalachians. Wetlands 25:130–142. https://doi.org/10.1672/0277-5212(2005)025[0130:ACOPCI]2.0.CO;2

Boschetti, M., F. Nutini, P. A. Brivio, E. Bartholome, D. Stoppiana, and A. Hoscilo. 2013. Identification of environmental anomaly hot spots in West Africa from time series of NDVI and rainfall. ISPRS Journal of Photogrammetry and Remote Sensing 78:26-40. https://doi.org/10.1016/j.isprsjprs.2013.01.003

Chakraborty, A., M. Seshasai, C. S. Reddy, and V. K. Dadhwal. 2018. Persistent negative changes in seasonal greenness over different forest types of India using MODIS time series NDVI data (2001–2014). Ecological Indicators 85:887-903. https://doi.org/10.1016/j.ecolind.2017.11.032

Cook, N. A., E. A. Sarver, L. H. Krometis, and J. Huang. 2015. Habitat and water quality as drivers of ecological system health in Central Appalachia. Ecological Engineering 84:180-189. https://doi.org/10.1016/j.ecoleng.2015.09.006

Drusch, M., U. Del Bello, S. Carlier, O. Colin, V. Fernandez, F. Gascon, B. Hoersch, C. Isola, P. Laberinti, P. Martimort, et al. 2012. Sentinel-2: ESA's optical high-resolution mission for GMES Operational Services. Remote Sensing of the Environment 120:25-36. https://doi.org/10.1016/j.rse.2011.11.026

Eklundh, L. R. 1995. Noise estimation in NOAA AVHRR maximum-value composite NDVI images. International Journal of Remote Sensing 16:2955-2962. https://doi.org/10.1080/01431169508954601

Fleming, G. P., and K. D. Patterson. 2017. The natural communities of Virginia: Ecological groups and community types. Natural Heritage Technical Report 17-07. Virginia Department of Conservation and Recreation, Division of Natural Heritage, Richmond, Virginia. 36 pp.

Franke, J., and G. Menz. 2007. Multi-temporal wheat disease detection by multi-spectral remote sensing. Precision Agriculture 8:161-172. https://doi.org/10.1007/s11119-007-9036-y

Fritsch, A. J., and K. Johannsen. 2014. Ecotourism in Appalachia: Marketing the Mountains. University Press of Kentucky, Lexington, Kentucky. 320 pp.

Getis, A., and J. K. Ord. 1992. The analysis of spatial association by use of distance statistics. Geographical Analysis 24:189-206. https://doi.org/10.1007/978-3-642-01976-0_10

Goward, S. N., B. Markham, D. G. Dye, W. Dulaney, and J. Yang. 1991. Normalized difference vegetation index measurements from the Advanced Very High Resolution Radiometer. Remote Sensing of the Environment 35:257-277. https://doi.org/10.1016/0034-4257(91)90017-Z

Hackbert, P. H. and X. Lin. 2009. Equestrian trail riding: An emerging economic contributor to the local rural Appalachian economy. Journal of Business Case Studies 5:47-58. https://doi.org/10.19030/jbcs.v5i6.4732

Hannaford, M. J., and V. H. Resh. 1999. Impact of all-terrain vehicles (ATVs) on pickleweed (*Salicornia virginica* L.) in a San Francisco Bay wetland. Wetlands Ecology and Management 7:225-233. https://doi.org/10.1023/A:1008482427472

Hinkel, K. M., W. R. Eisner, and C. J. Kim. 2017. Detection of tundra trail damage near Barrow, Alaska using remote imagery. Geomorphology 293:360-367. https://doi.org/10.1016/j.geomorph.2016.09.013

Holben, B. N. 1986. Characteristics of maximum-value composite images from temporal AVHRR data. International Journal of Remote Sensing 7:1417-1434. https://doi.org/10.1080/01431168608948945

Iverson, R. M., B. S. Hinckley, and R. M. Webb. 1981. Physical effects of vehicular disturbances on arid landscapes. Science 212:915–917. http://dx.doi.org/10.1126/science.212.4497.915

Jaramillo, E., N. A. Lagos, F. A. Labra, E. Paredes, E. Acuna, D. Melnick, M. Manzano, C. Velasquez, and C. Duarte. 2018. Recovery of black-necked swans, macrophytes and water quality in a Ramsar wetland of southern Chile: Assessing resilience following sudden anthropogenic disturbances. Science of the Total Environment 628:291-301. https://doi.org/10.1016/j.scitotenv.2018.01.333

Kayastha, N., V. Thomas, J. Galbraith, and A. Banskota. 2012. Monitoring wetland change using inter-annual Landsat time-series data. Wetlands 32:1149-1162. http://doi.org/10.1007/s13157-012-0345-1

Kiviat, E. 2013. Risks to biodiversity from hydraulic fracturing for natural gas in the Marcellus and Utica Shales. Annals of the New York Academy of Sciences 1286:1-14. https://doi.org/10.1111/nyas.12146

Liddle, M. J. 1997. Recreation ecology—The ecological impact of outdoor recreation and ecotourism. Chapman and Hall, London. 666 pp.

Lovich, J. E., and D. Bainbridge. 1999. Anthropogenic degradation of the southern California desert ecosystem and prospects for natural recovery and restoration. Environmental Management 24:309-326. https://doi.org/10.1007/s002679900235

Lumbierres, M., P. F. Mendez, J. Bustamante, R. Soriguer, and L. Santamaria. 2017. Modeling biomass production in seasonal wetlands using MODIS NDVI Land Surface Phenology. Remote Sensing 9:392. https://doi.org/10.3390/rs9040392

Maigret, T. A., John J. C., and J. Yang. 2019. Persistent geophysical effects of mining threaten ridgetop biota of Appalachian forests. Frontiers in Ecology and the Environment 17:85-91. https://doi.org/10.1002/fee.1992

Mayer, A. L., and R. D. Lopez. 2011. Use of remote sensing to support forest and wetlands policies in the USA. Remote Sensing 3:1211-1233. https://doi.org/10.3390/rs3061211

Meyer, K. G. 2002. Managing Degraded Off-Highway Vehicle Trails in Wet, Unstable, and

Sensitive Environments. United States Department of Agriculture Forest Service, Technology and Development Program, Missoula, Montana. 56 pp.

Miller, A., and N. Zegre. 2016. Landscape-scale disturbance: Insights into the complexity of catchment hydrology in the mountaintop removal mining region of the eastern United States. Land 5:22. https://doi.org/10.3390/land5030022

Ouren, D. S., C. Haas, C. P. Melcher, S. C. Stewart, P. D. Ponds, N. R. Sexton, L. Burris, T. Fancher, and Z. R. Bowen. 2009. Environmental Effects of Off-Highway Vehicles on Bureau of Land Management Lands: A Literature Synthesis, Annotated Bibliographies, Extensive Bibliographies, and Internet Resources. United States Geological Survey, Reston, Virginia. 242 pp.

Ozesmi, S. L. and M. E. Bauer. 2002. Satellite remote sensing of wetlands. Wetlands Ecology and Management 10:381-402. https://doi.org/10.1023/A:1020908432489

Pettorelli, N., J. O. Vik, A. Mysterud, J-M. Gaillard, C. J. Tucker, and N. C. Stenseth. 2005. Using the satellite-derived NDVI to assess ecological responses to environmental change. Trends in Ecology and Evolution 20:503-510. https://doi.org/10.1016/j.tree.2005.05.011

Petty, J. T., G. Gingerich, J. T. Anderson, and P. F. Ziemkiewicz. 2013. Ecological function of constructed perennial stream channels on reclaimed surface coal mines. Hydrobiologia 720:39-53. https://doi.org/10.1007/s10750-013-1619-1

Piao, S., A. Mohammat, J. Fang, Q. Cai, and J. Feng. 2006. NDVI-based increase in growth of temperate grasslands and its responses to climate changes in China. Global Environmental Change 16:340-348. https://doi.org/10.1016/j.gloenvcha.2006.02.002

Potter, C. 2018. Recovery Rates of Wetland Vegetation Greenness in Severely Burned Ecosystems of Alaska Derived from Satellite Image Analysis. Remote Sensing 10:1456 https://doi.org/10.3390/rs10091456

Rodgers, J. C., A. W. Murrah, and W. H. Cocke. 2009. The impact of Hurricane Katrina on the coastal vegetation of the Weeks Bay Reserve, Alabama from NDVI data. Estuaries and Coasts 32:496-507. https://doi.org/10.1007/s12237-009-9138-z

Ross, M. R. V., B. L. McGlynn, and E. S. Bernhardt. 2016. Deep impact: Effects of mountaintop mining on surface topography, bedrock structure, and downstream waters. Environmental Science and Technology 50:2064–2074. https://doi.org/10.1021/acs.est.5b04532

Saylor, K. L. 2008. Land Cover Trends: Central Appalachians. United States Geological Survey, Reston, Virginia. 11 pp.

Scott, R. R. 2010. Removing Mountains: Extracting Nature and Identity in the Appalachian Coalfields. University of Minnesota Press, Minneapolis, Minnesota. 271 pp.

Scott, S. L., S. McSpirit, and J. Foley. 2017. Promoting outdoor recreation and adventure tourism on the Russell Fork: An academic-community partnership report. Journal of Appalachian Studies 23:170-180. https://doi.org/10.5406/jappastud.23.2.0170

Sharp, R., M. J. Bradley, and J. Maples. 2020. Who has the right-of-way? Negotiating environmental and economic impacts of off-highway vehicle use in eastern Kentucky. Journal of Appalachain Studies 26:191-208. https://doi.org/10.5406/jappastud.26.2.0191

Snyder, S. A., J. H. Whitmore, I. E. Schneider, and D. R. Becker. 2008. Ecological criteria, participant preferences and location models: A GIS approach toward ATV trail planning. Applied Geography. 28:248-258. https://doi.org/10.1016/j.apgeog.2008.07.001

Sobczak, R. V., and A. J. Pernas. 2002. Re-evaluation of off-road vehicle management in Big Cypress National Preserve, Florida, after twenty-six years of management. Florida Scientst 65:100-114.

Stephens, K., J. Sencindiver, and J. Skousen. 2015. Characteristics of wetland soils impacted by acid mine drainage. Southeastern Naturalist. 14:40-57. https://doi.org/10.1656/058.014.sp707

Taddeo, S., I. Dronova, and K. Harris. 2019. The potential of satellite greenness to predict plant diversity among wetland types, ecoregions, and disturbance levels. Ecological Applications 29:e01961. https://doi.org/10.1002/eap.1961

Taylor, B. R., and S. Raney. 2013. Correlation between ATV tracks and density of a rare plant (*Drosera filiformis*) in a Nova Scotia Bog. Rhodora 115:158-169. https://doi.org/10.3119/12-10

Thompson, Y., B. C. Sandefur, J. O. Miller, and A.D. Karathanasis. 2007. Hydrologic and edaphic characteristics of three mountain wetlands in southeastern Kentucky, USA. Wetlands 27:174-188. https://doi.org/10.1672/0277-5212(2007)27[174:HAECOT]2.0.CO;2

Thompson, Y., E.M. D'Angelo, A.D. Karathanasis, and B. C. Sandefur. 2012. Plant community composition as a function of geochemistry and hydrology in three Appalachian wetlands. Ecohydrology 5:389-400. https://doi.org/10.1002/eco.228

Townsend, P. A., D. P. Helmers, C. C. Kingdon, B. E. McNeil, K. M. de Beurs, and K. N. Eshleman. 2009. Changes in the extent of surface mining and reclamation in the Central Appalachians detected using a 1976–2006 Landsat time series. Remote Sensing of the Environment 113:62–72. https://doi.org/10.1016/j.rse.2008.08.012

Trip, N. V. V., and Y. F. Wiersma. 2015. A comparison of all-terrain vehicle (ATV) trail impacts on boreal habitats across scales. Natural Areas Journal 35:266-278. https://doi.org/10.3375/043.040.0310

United States Department of Agriculture Forest Service. 2004. Revised Land and Resource Management Plan, Jefferson National Forest. Management Bulletin R8-MB 115A. Roanoke, Virginia. 396 pp.

United States Fish and Wildlife Service. 2016. Threatened Species Status for the Big Sandy Crayfish and Endangered Species Status for the Guyandotte River Crayfish. United States Federal Register, 20449-20481.

Vanderhoof, M. K., J. Christensen, Y-J. G. Beal, B. DeVries, M. W. Lang, N. Hwang, C. Mazzarella, and J. W. Jones. 2020. Isolating Anthropogenic Wetland Loss by Concurrently Tracking Inundation and Land Cover Disturbance across the Mid-Atlantic Region, U.S. Remote Sensing 12:1464. https://doi.org/10.3390/rs12091464

Virginia Geographic Information Network. 2019. Virginia Base Mapping Program Orthoimagery. Chester, VA. https://vgin.maps.arcgis.com/home/index.html. (Accessed 12 January 2020).

Webb, R. H., and H. G. Wilshire. 1983. Environmental effects of off-road vehicles—Impacts and management in arid regions. Springer-Verlag, New York.

Weber, J. T., and J. F. Bulluck. 2014. Virginia Wetlands Catalog: An Inventory of Wetlands and Potential Wetlands with Prioritization Summaries for Conservation and Restoration Purposes by Parcel, Subwatershed, and Wetland Boundaries. Natural Heritage Technical Report 14-4. Virginia Department of Conservation and Recreation, Division of Natural Heritage. Richmond, Virginia 49 pp.

Welch, R., M. Madden, and B. Doren. 2002. Maps and GIS databases for environmental studies of the Everglades. P. 259-279 in Porter, J. W. & K. G. Porter (eds.), The Everglades, Florida Bay and Coral Reefs of the Florida Keys, an Ecosystem Sourcebook. CRC Press, Boca Raton Florida.

Wickham, J., P. B. Wood, M. C. Nicholson, W. Jenkins, D. Druckenbrod, G. W. Suter, M. P. Strager, C. Mazzarella, W. Galloway, and J. Amos. 2013. The overlooked terrestrial impacts of mountaintop mining. BioScience 63:335-348. https://doi.org/10.1525/bio.2013.63.5.7

Wilson, N. R., and L. M. Norman. 2018. Analysis of vegetation recovery surrounding a restored wetland using the normalized difference infrared index (NDII) and normalized difference vegetation index (NDVI). International Journal of Remote Sensing 39:3243-3274. https://doi.org/10.1080/01431161.2018.1437297

Xu, P., Z. Niu, and P. Tang. 2017. Comparison and assessment of NDVI time series for seasonal wetland classification. International Journal of Digital Earth 11:1103-1131. https://doi.org/10.1080/17538947.2017.1375563

Zhao, B., Y. Yan, H. Guo, M. He, Y. Gu, and B. Li. 2009. Monitoring rapid vegetation succession in estuarine wetland using time series MODIS-based indicators: An application in the Yangtze River Delta area. Ecological Indicators 9:346-356. https://doi.org/10.1016/j.ecolind.2008.05.009

Zoffoli, M. L., P. Kandus, N. Madanes, and D. H. Calvo. 2008. Seasonal and interannual analysis of wetlands in South America using NOAA-AVHRR NDVI time series: The case of the Parana Delta Region. Landscape Ecology 23:833-848. https://doi.org/10.1007/s10980-008-9240-9